

Data assimilation at ECMWF

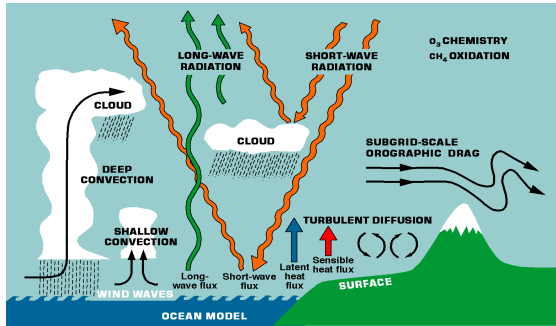
Massimo Bonavita

ECMWF

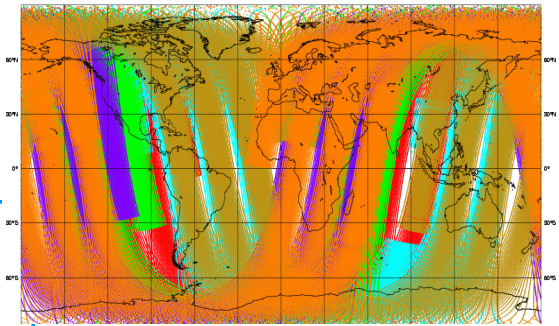
Data Assimilation Section

massimo.bonavita@ecmwf.int

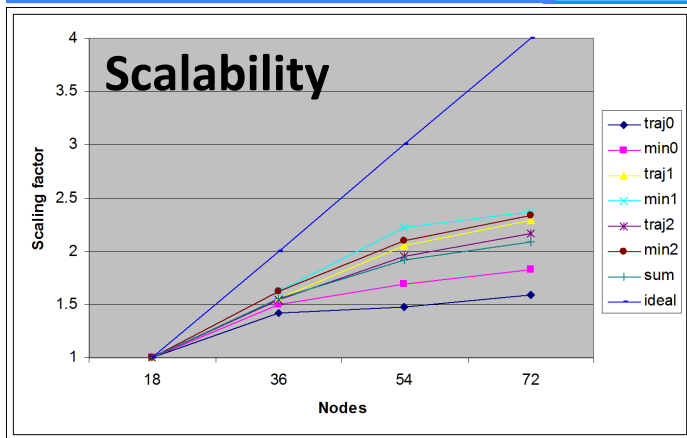
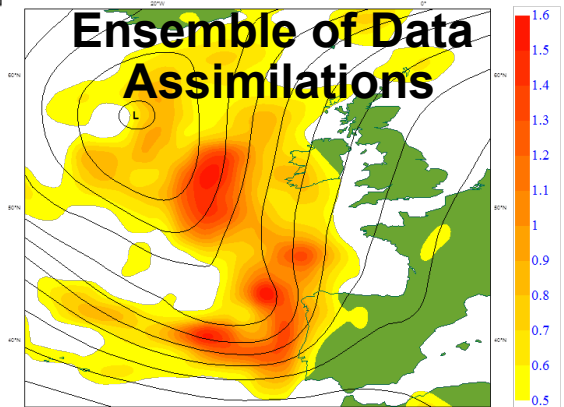
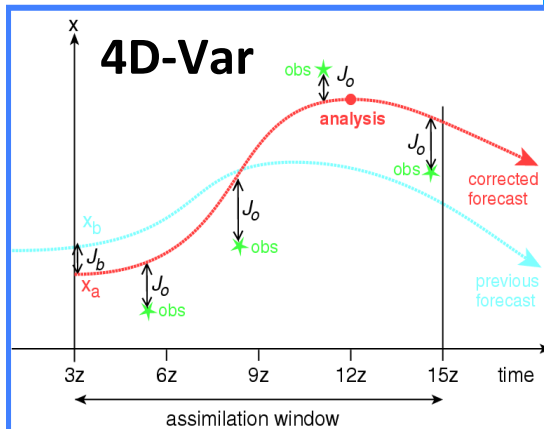
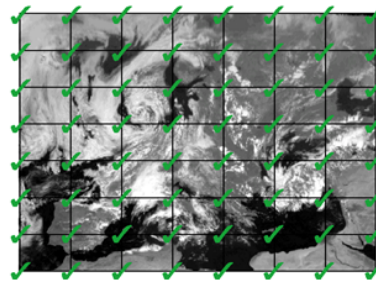
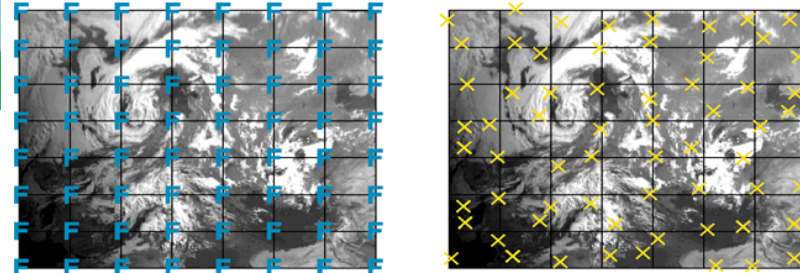
Data assimilation at ECMWF



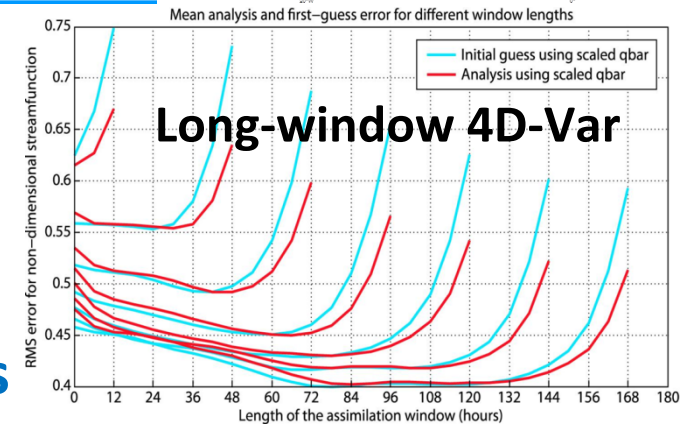
Forecast model



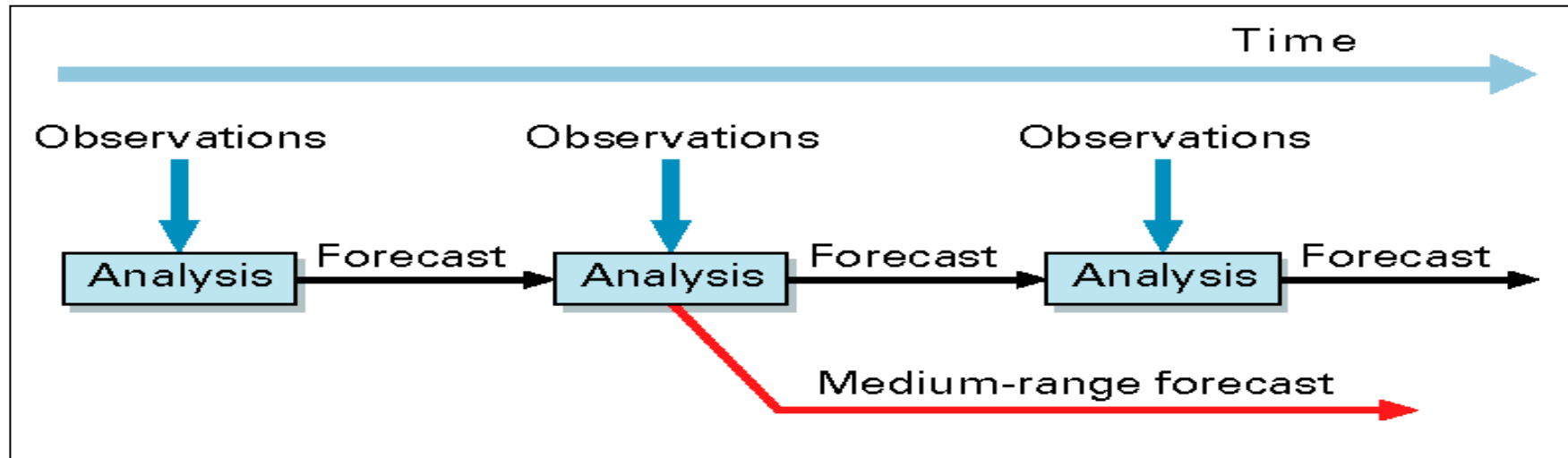
Observations



Methods Progress and plans



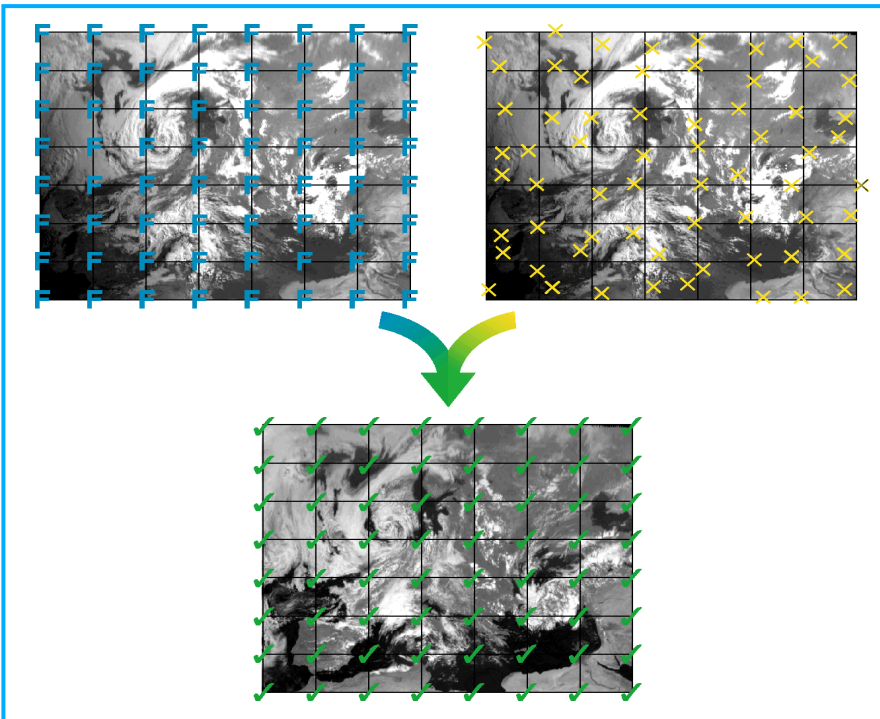
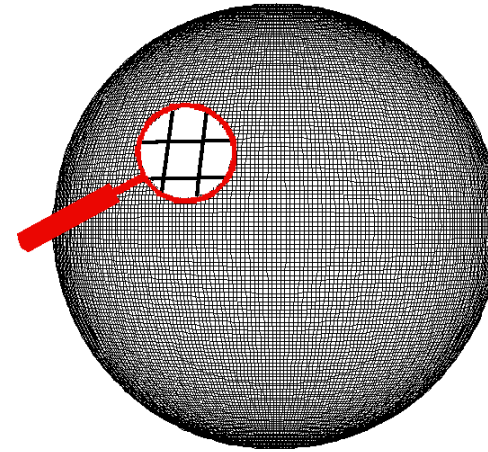
Data assimilation



- The observations are used to correct errors in the short forecast from the previous analysis time.
- At ECMWF, twice a day 15 – 16,000,000 observations are used to correct the 80,000,000 variables that define the model's virtual atmosphere.
- This is done by a careful 4-dimensional interpolation in space and time of the available observations; this operation takes as much computer power as the 10-day forecast.

Data assimilation for weather prediction

The **FORECAST** is computed on a quasi-regular grid over the globe.
The meteorological **OBSERVATIONS** come from any location on the globe.
The computer model's prediction of the atmosphere is compared against the available observations, in near real time



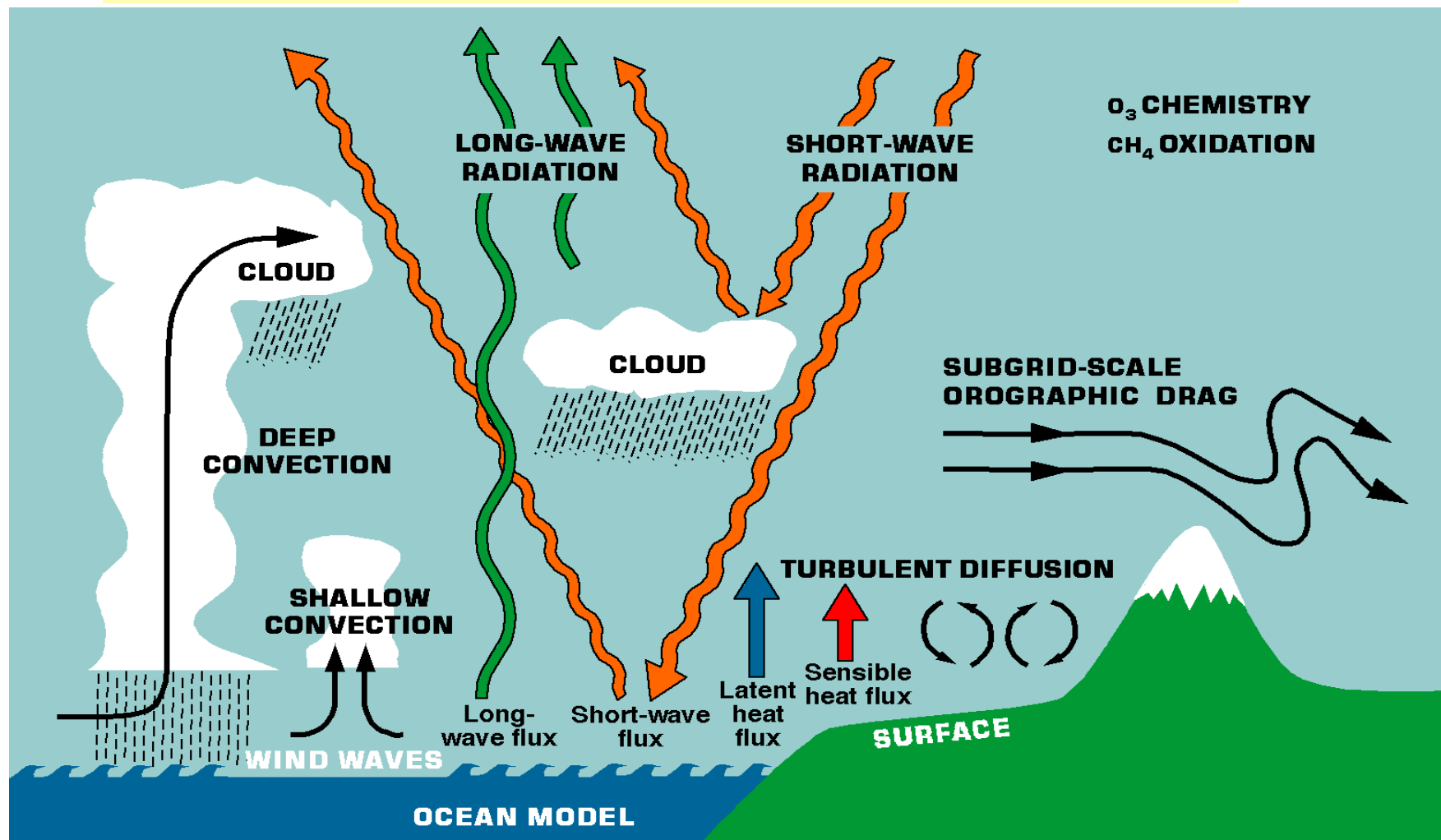
A short-range **forecast** provides an estimate of the atmosphere that is compared with the **observations**.

The two kinds of information are combined to form a corrected atmospheric state: the **analysis**.

Corrections are computed and applied twice per day. This process is called '**Data Assimilation**'.

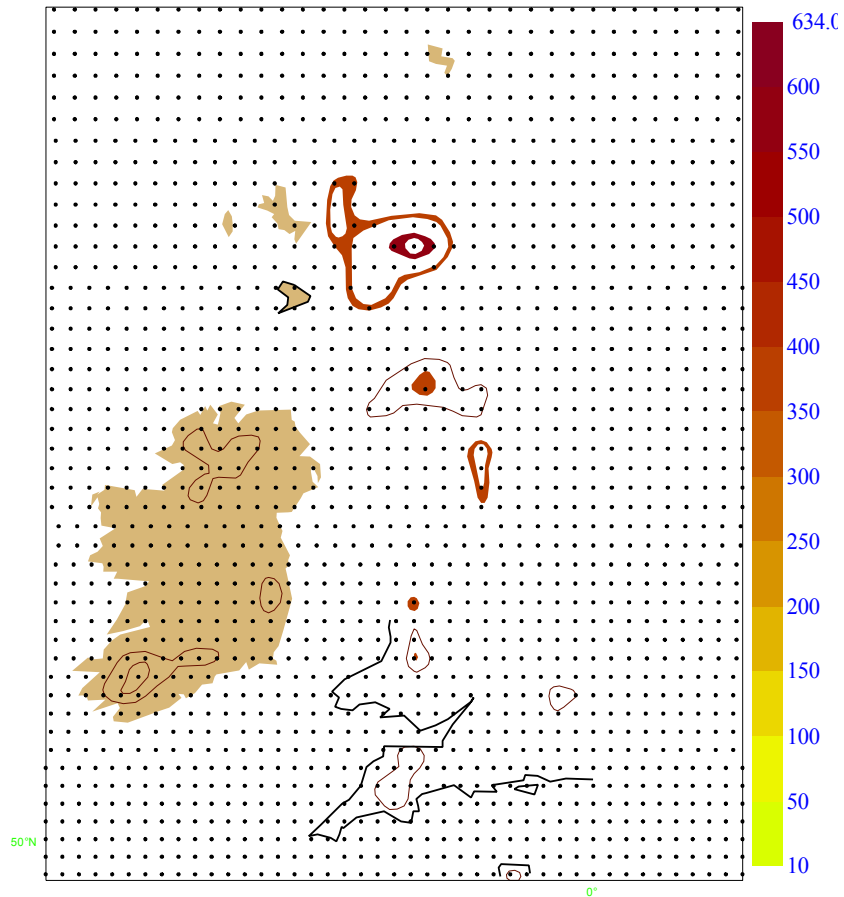
The ECMWF forecast model is a very important component of the data assimilation system

Physical processes in the ECMWF model



T_L799

Previous operational resolution

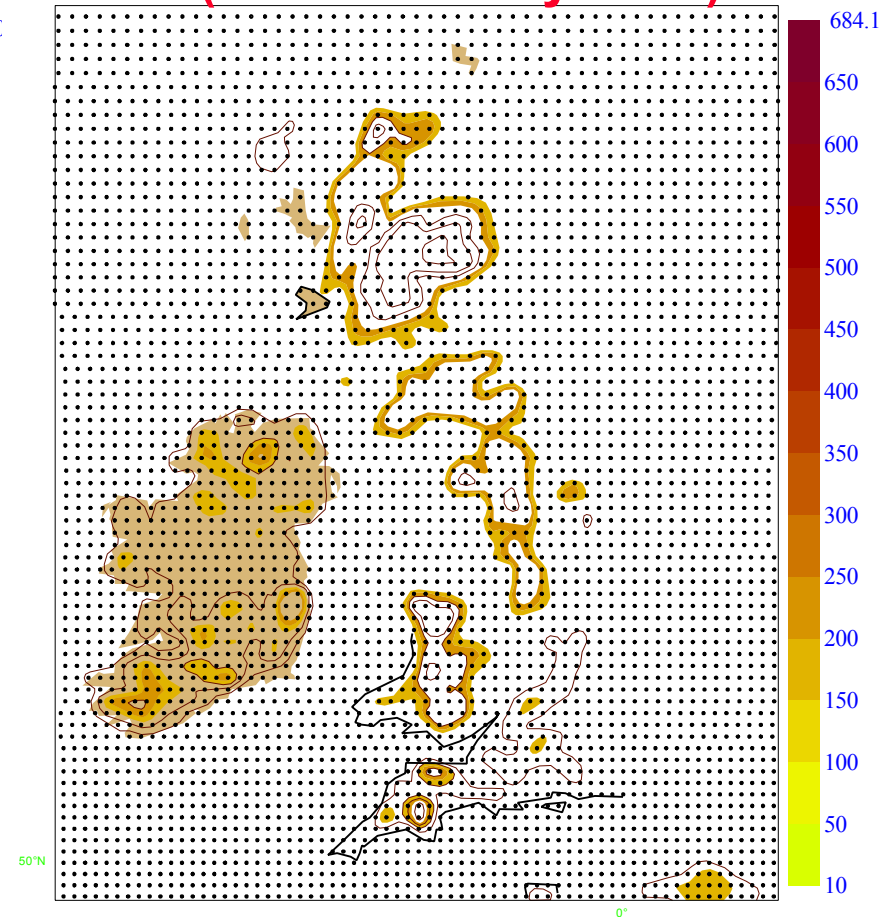


25 km grid-spacing

(843,490 grid-points)

T_L1279

**Current operational resolution
(since January 2010)**

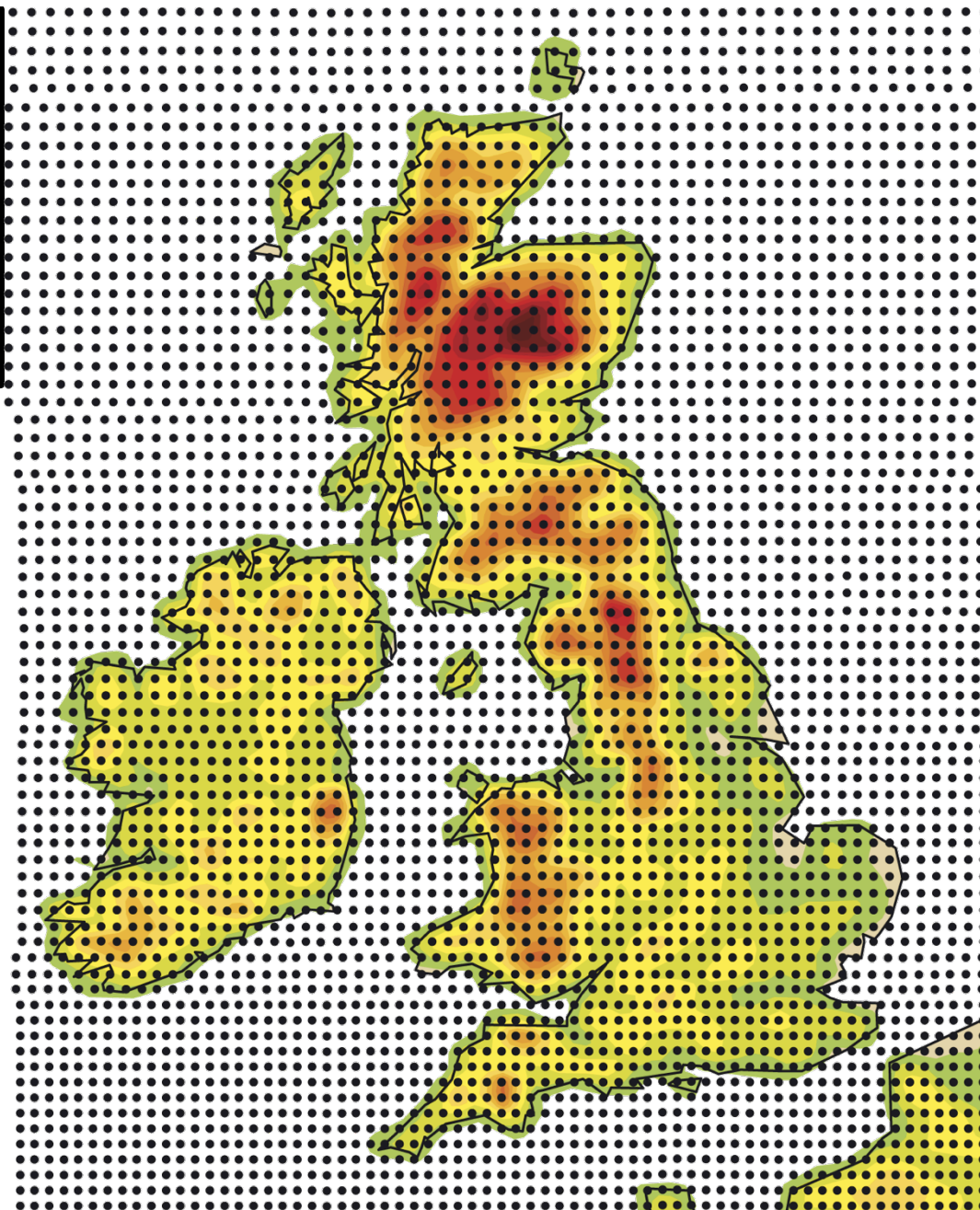
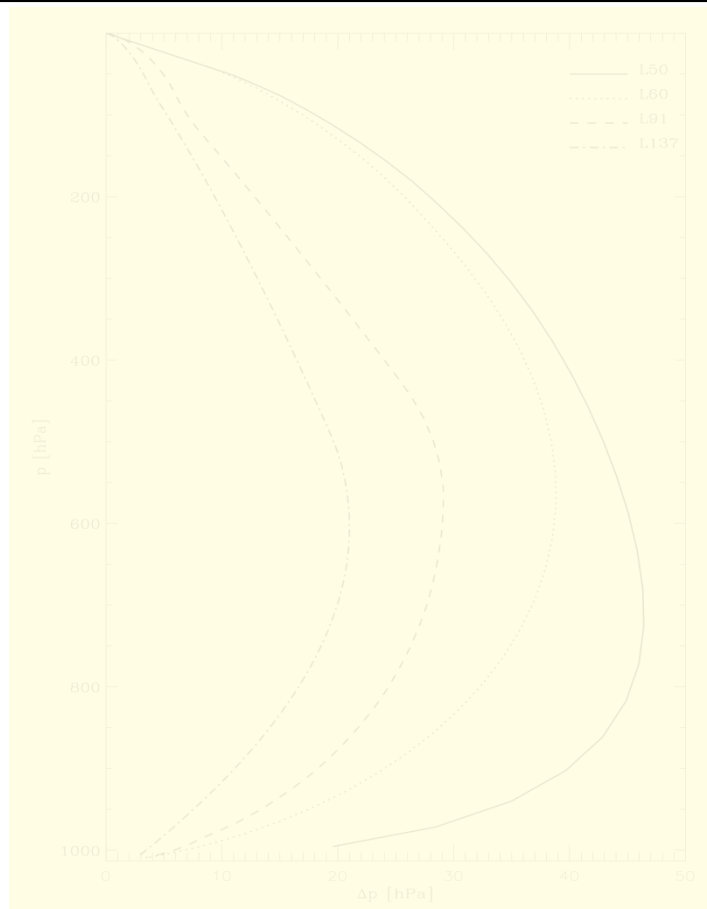


16 km grid-spacing

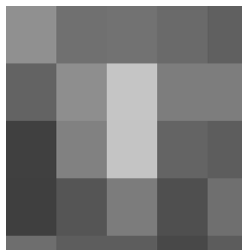
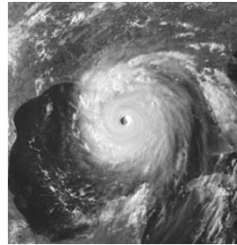
(2,140,704 grid-points)

Model resolution matters.

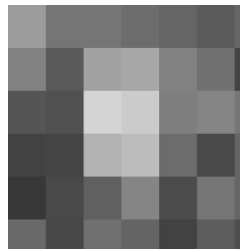
Present ECMWF system:
Global model with 16 km
resolution and 137 levels



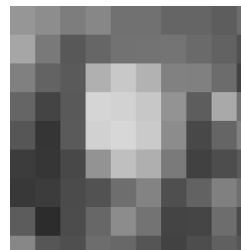
Increasing Resolution



~210km



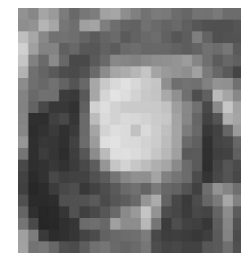
~125km



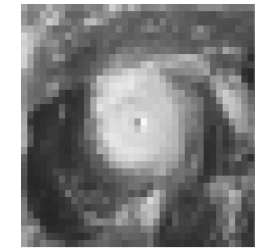
~63km



~39km

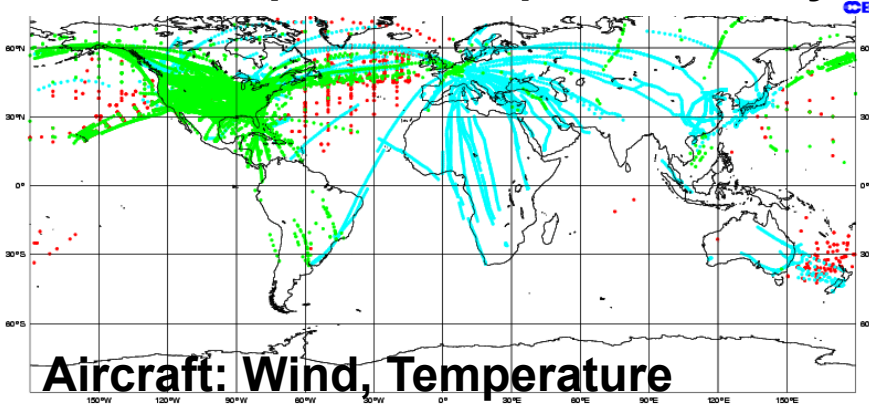
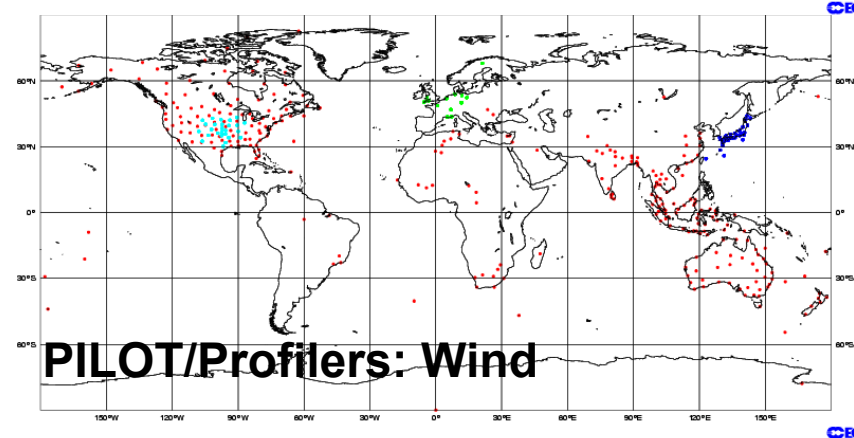
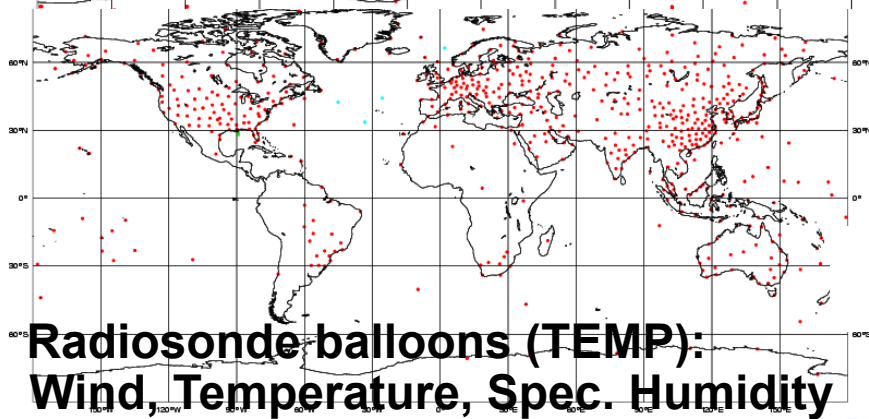
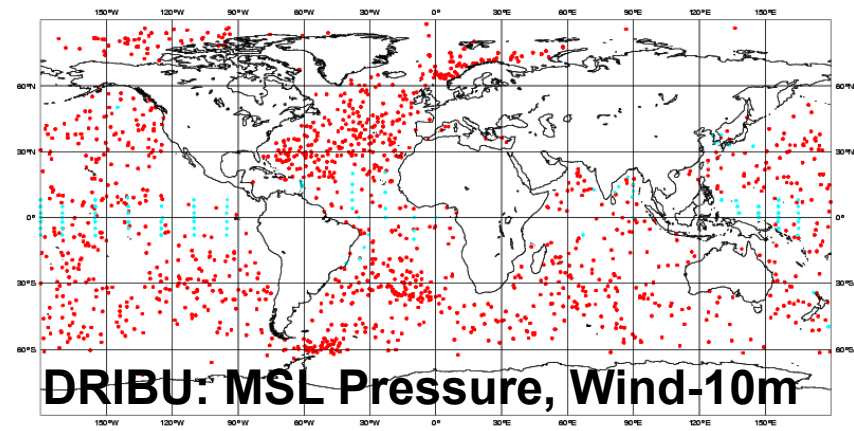
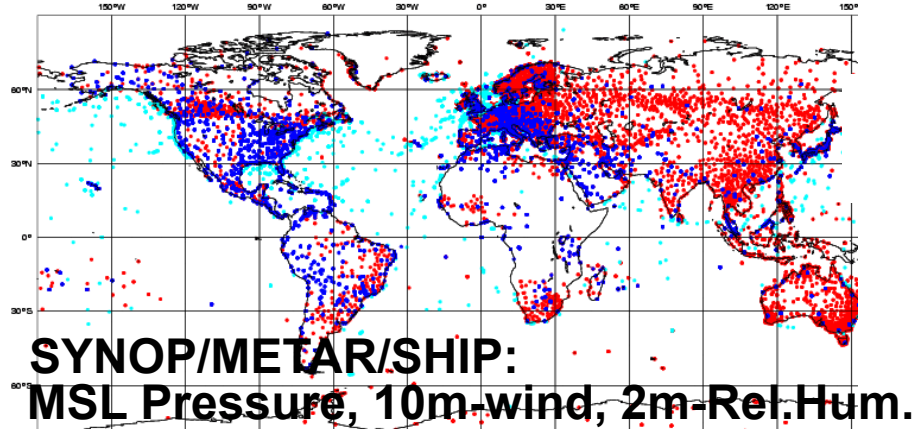


~25km



~16km

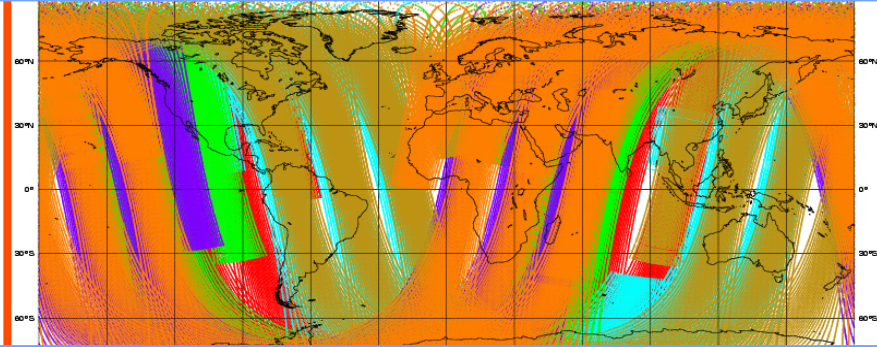
Conventional observations used by ECMWF's analysis



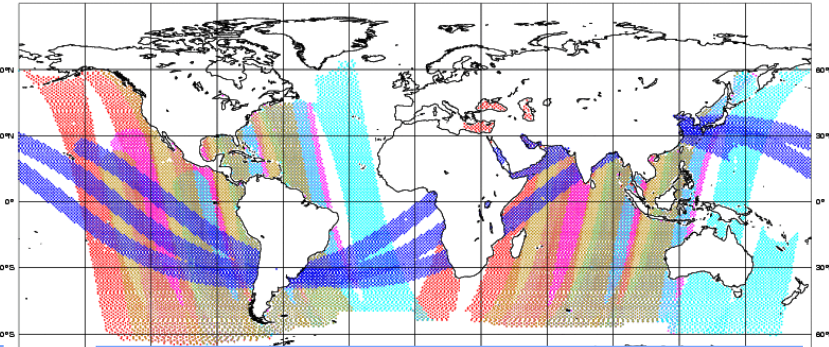
Note: We only use a limited number of the observed variables; especially over land.

Satellite data sources used by ECMWF's analysis

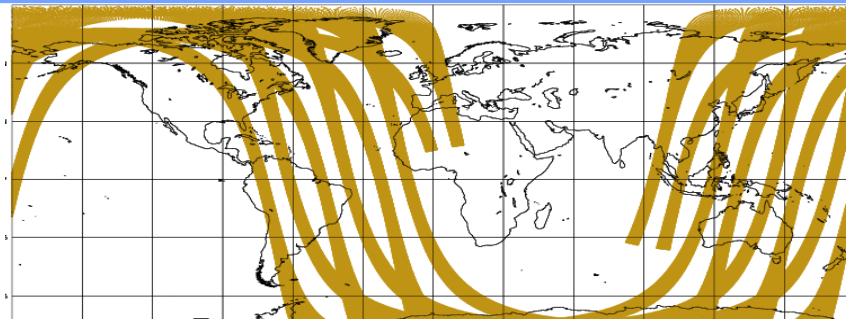
Sounders: NOAA AMSU-A/B, HIRS, AIRS, IASI, MHS



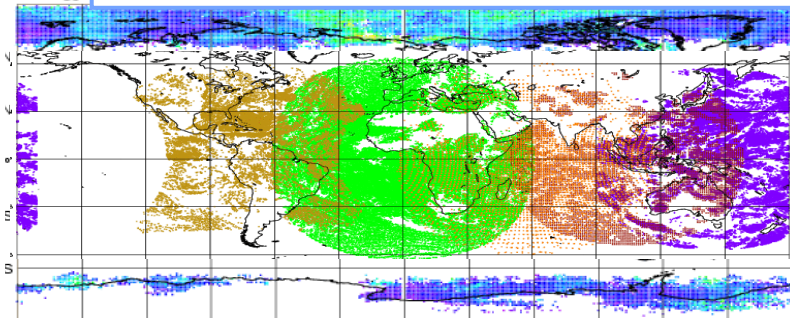
Imagers: SSMI, SSMIS, AMSR-E, TMI



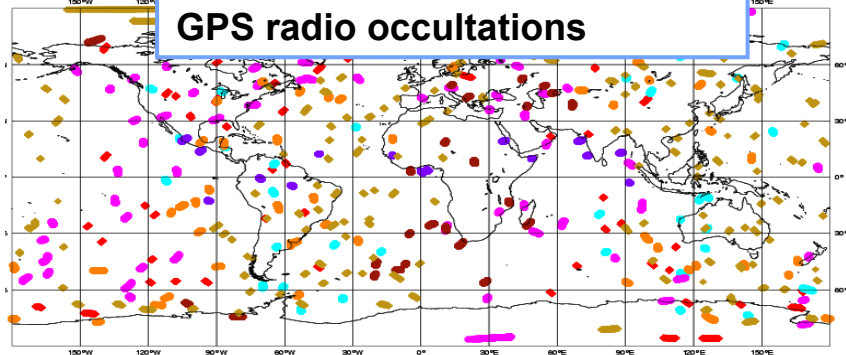
Scatterometer ocean low-level winds: ASCAT



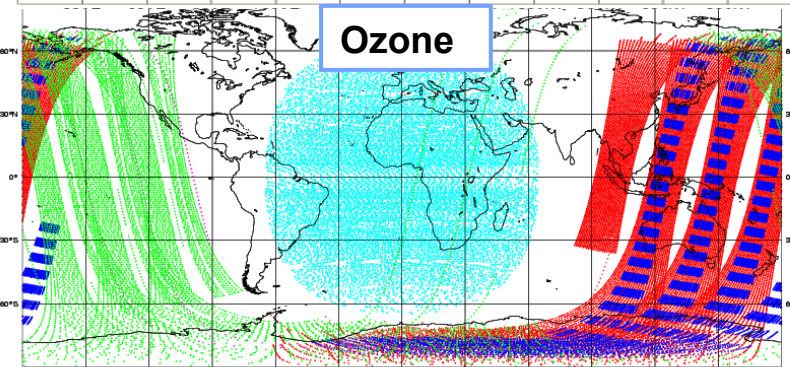
Geostationary+MODIS: IR and AMV



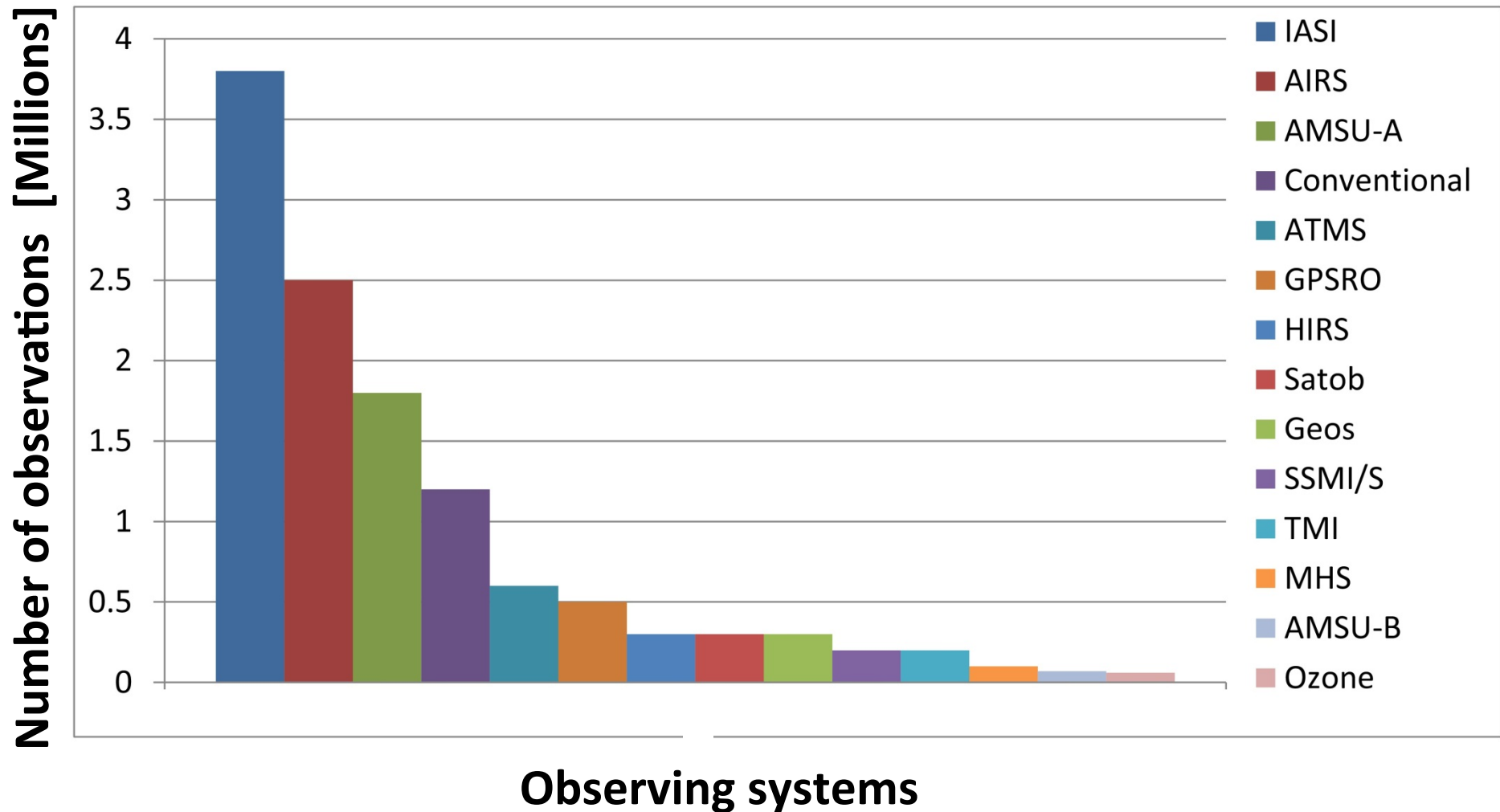
GPS radio occultations



Ozone

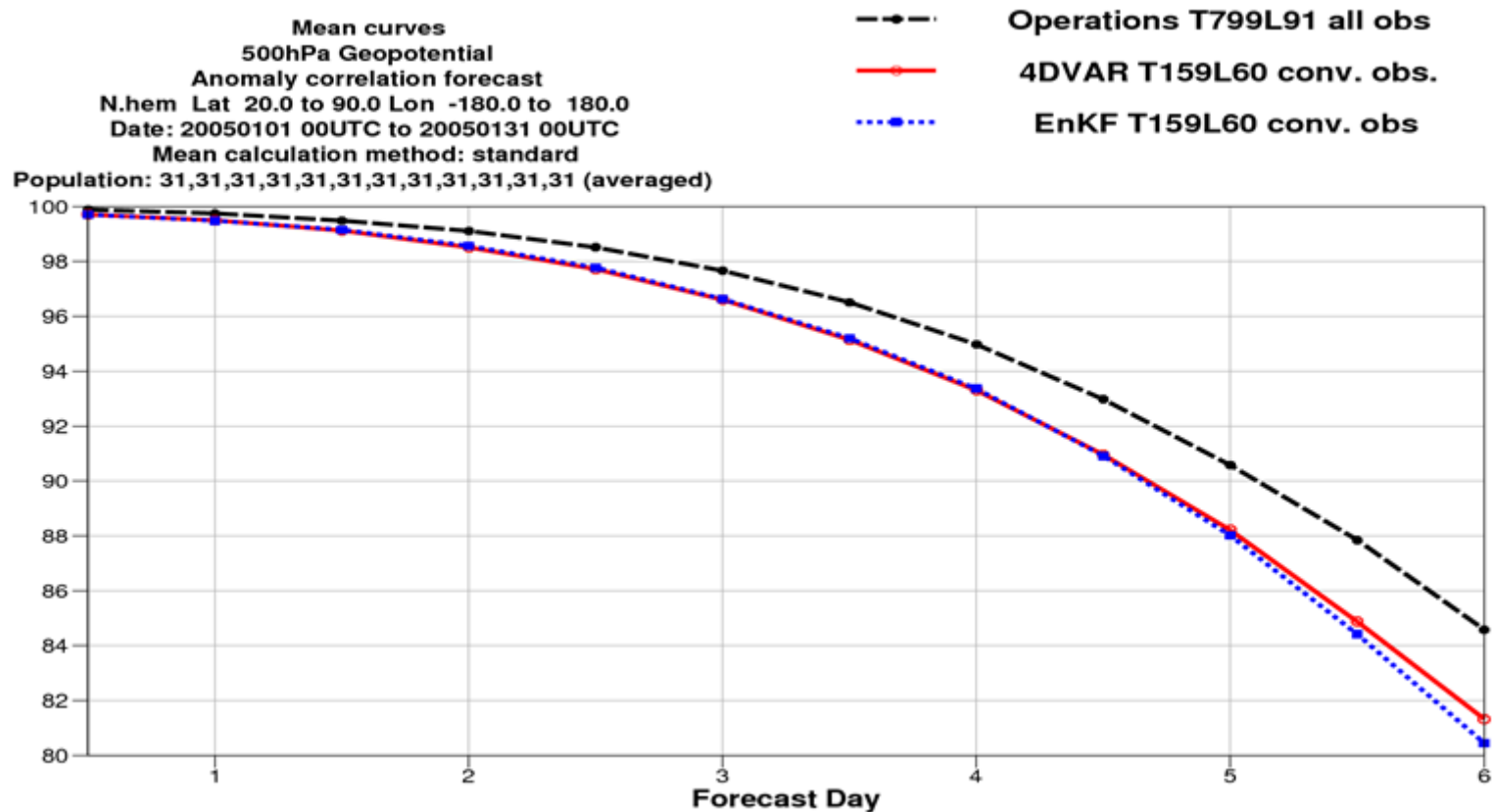


Number of observations used for a 12-hour 4D-Var analysis:
Total approx. 15M (conventional data approx. 1.2M)

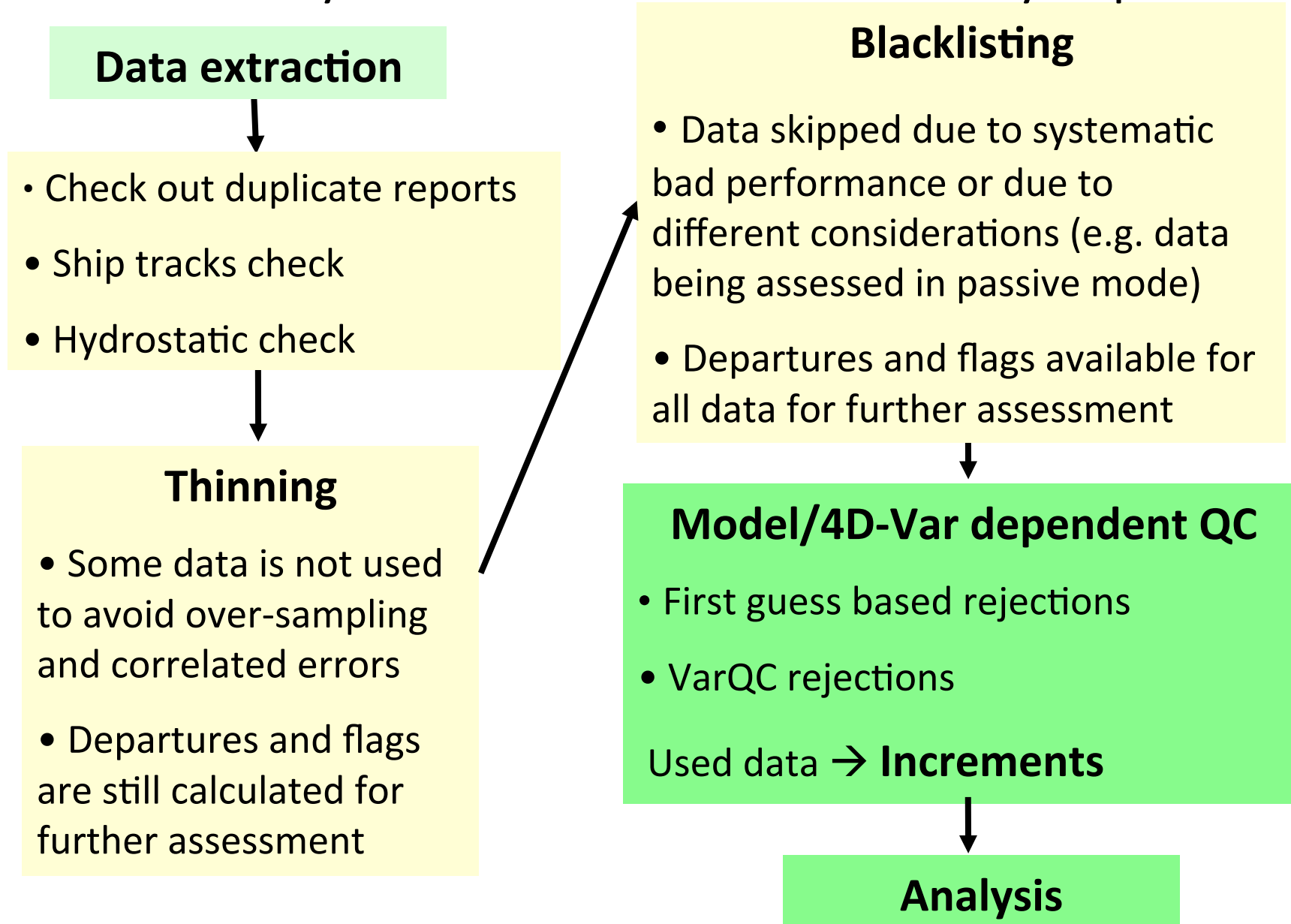


Observations

- **Satellite Obs.** make up $\approx 95\%$ of total used observations
- **Conventional Obs.** are still very important in the North Hem. and for the bias correction of the satellite radiances

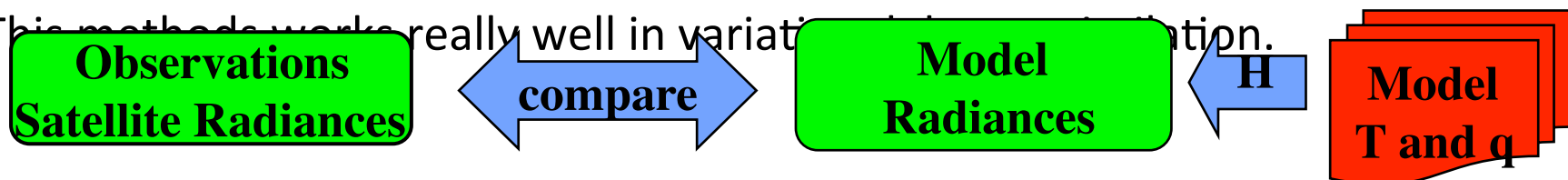


Quality control of observations is very important

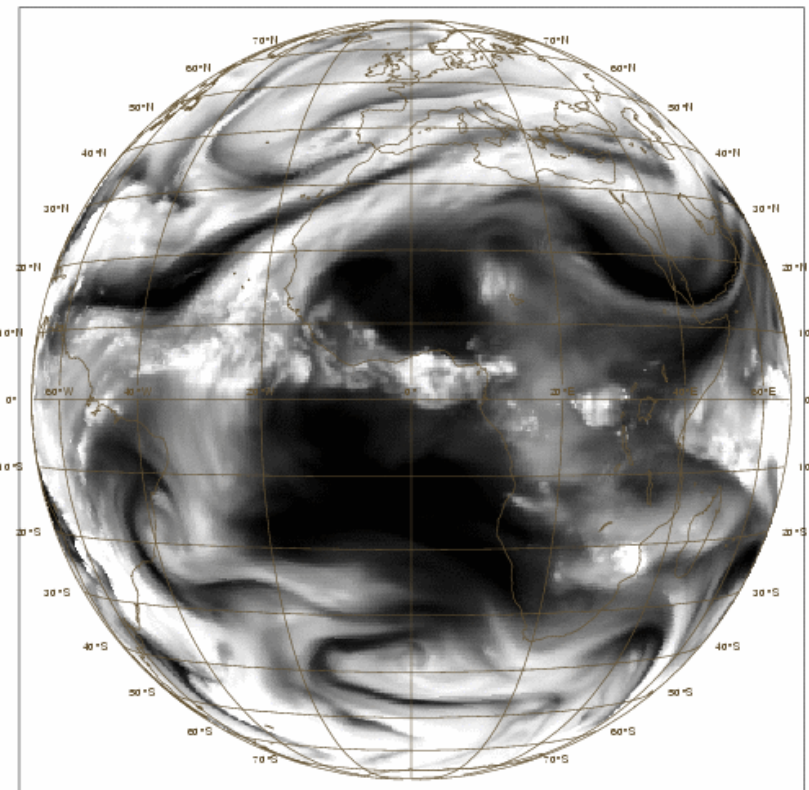
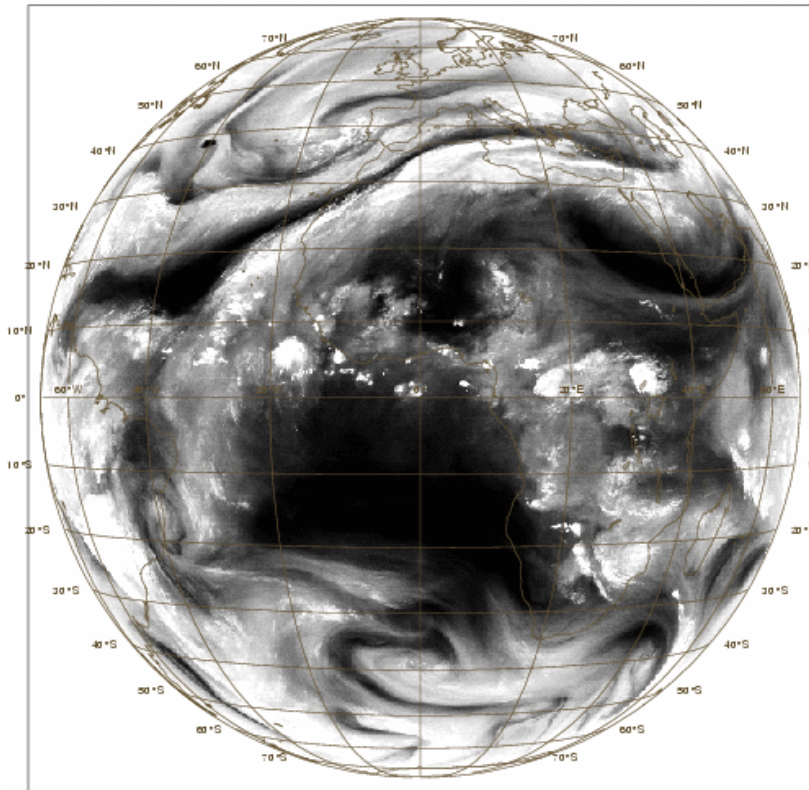
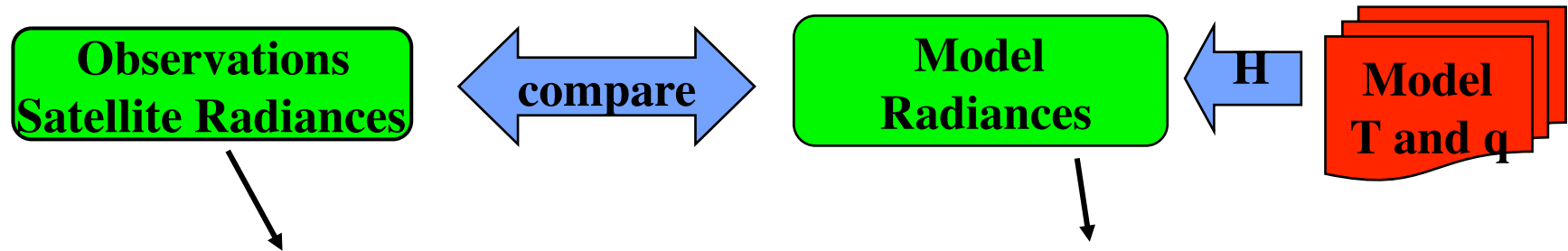


How we use satellite data in the analysis

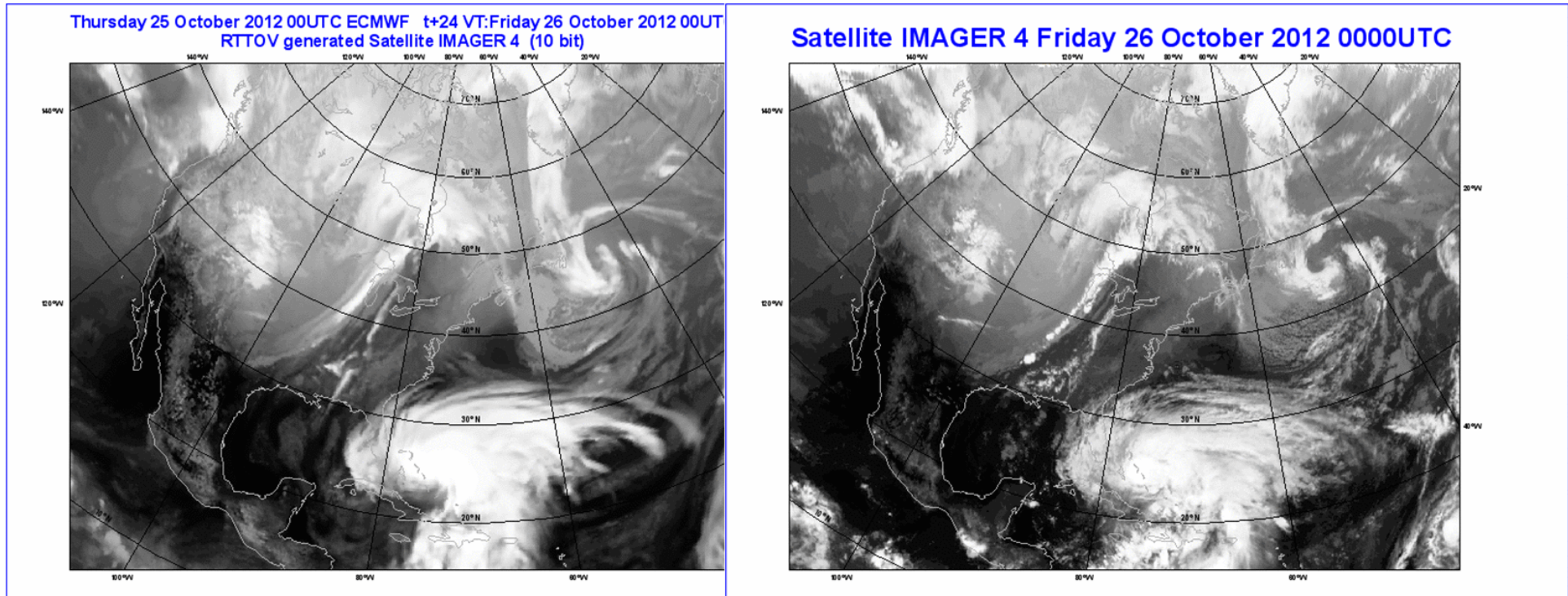
- Observations are not made at model grid points.
- Satellites measure radiances, NOT temperature and humidity .
- We calculate a model radiance estimate of the radiance measurement, using a so-called ‘observation operator’ **H**.
- **H** performs a complex transformations of model variables (T,q,O3) to radiances.
- The model estimate is compared with the observed radiance.
- The difference between the observed radiance and the radiance estimated by the model (background departure) is used in the analysis algorithm.
- This method works really well in variational data assimilation.



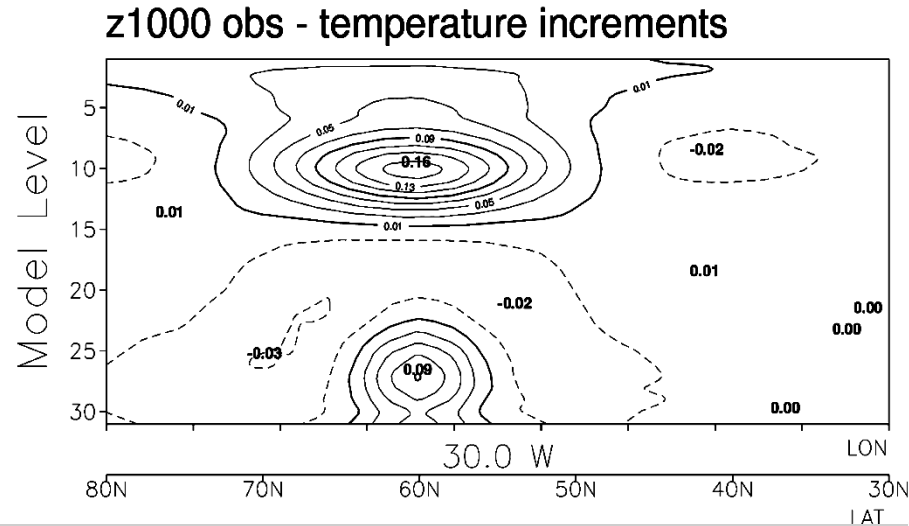
The variational method allows model radiances to be compared directly to observed radiances



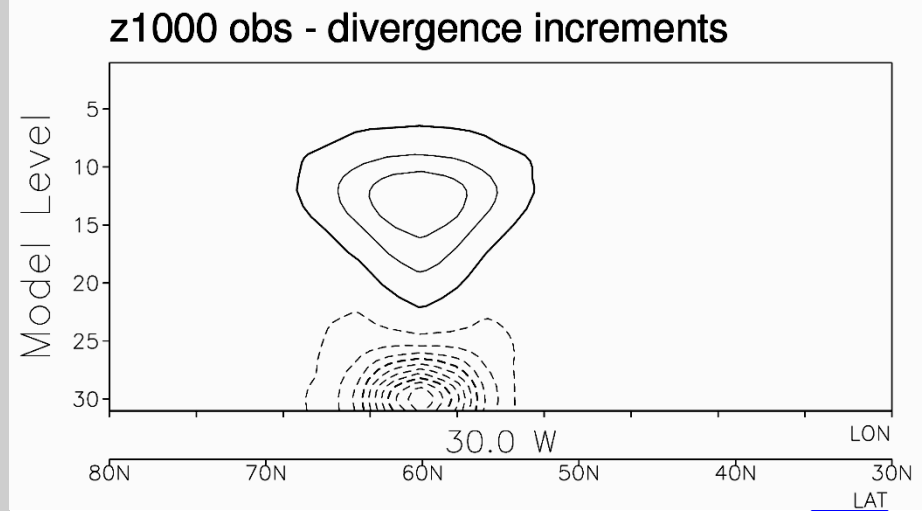
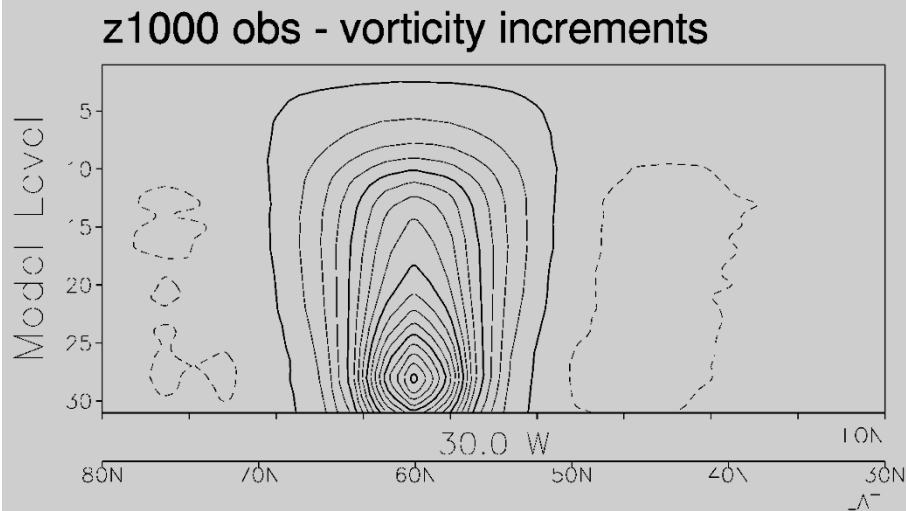
Hurricane Sandy 22-30 Oct. 2012



Analysis corrections are meteorologically consistent!



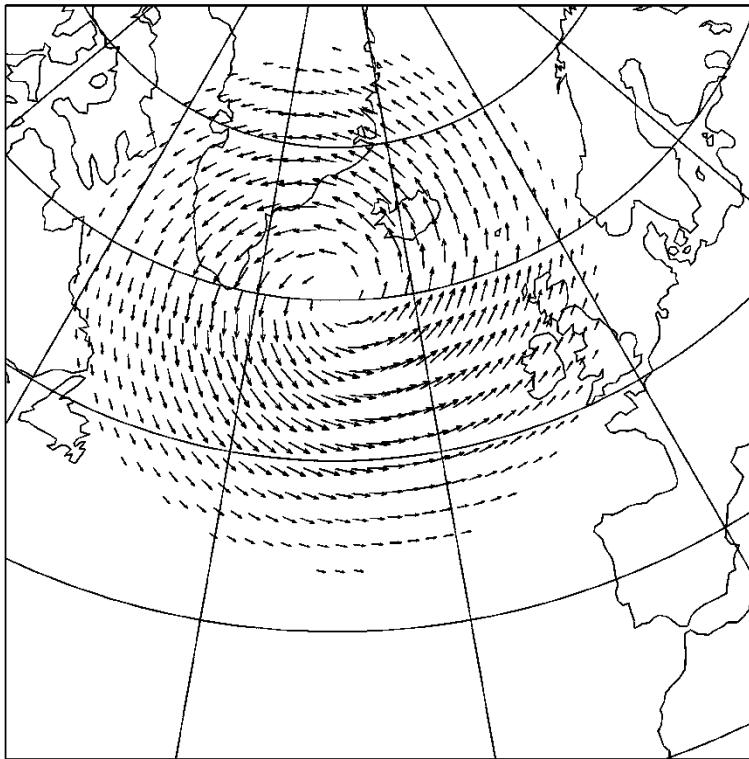
Increments due to a single observation of geopotential height at 1000hPa at 60N with value 10m below the background.



Analysis corrections are meteorologically consistent! Height and wind field balance is retained in the extra-tropics

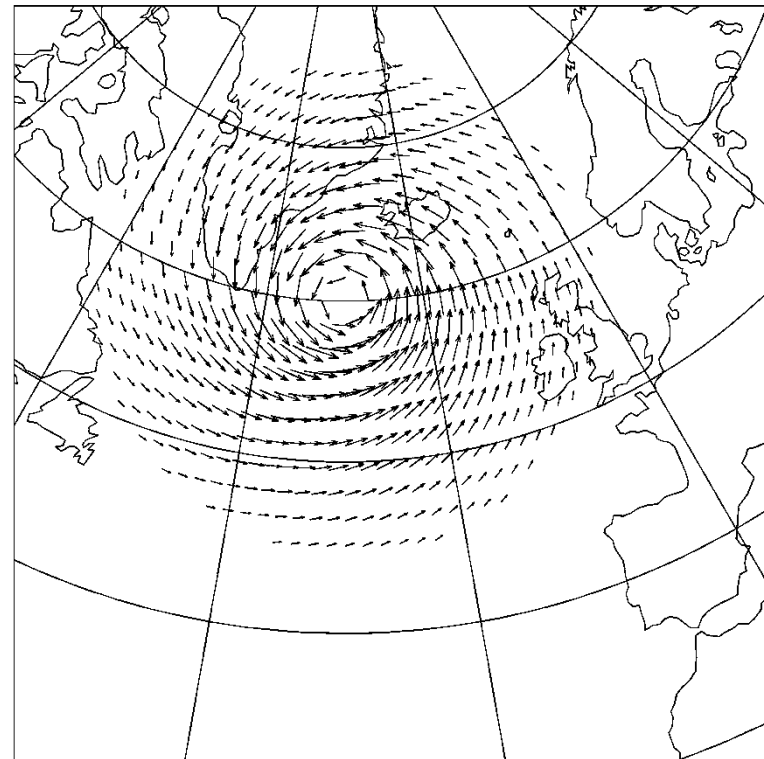
wind increments at 300hPa

→ 0.5 m/s



wind increments 150 metre above surface

→ 0.5 m/s

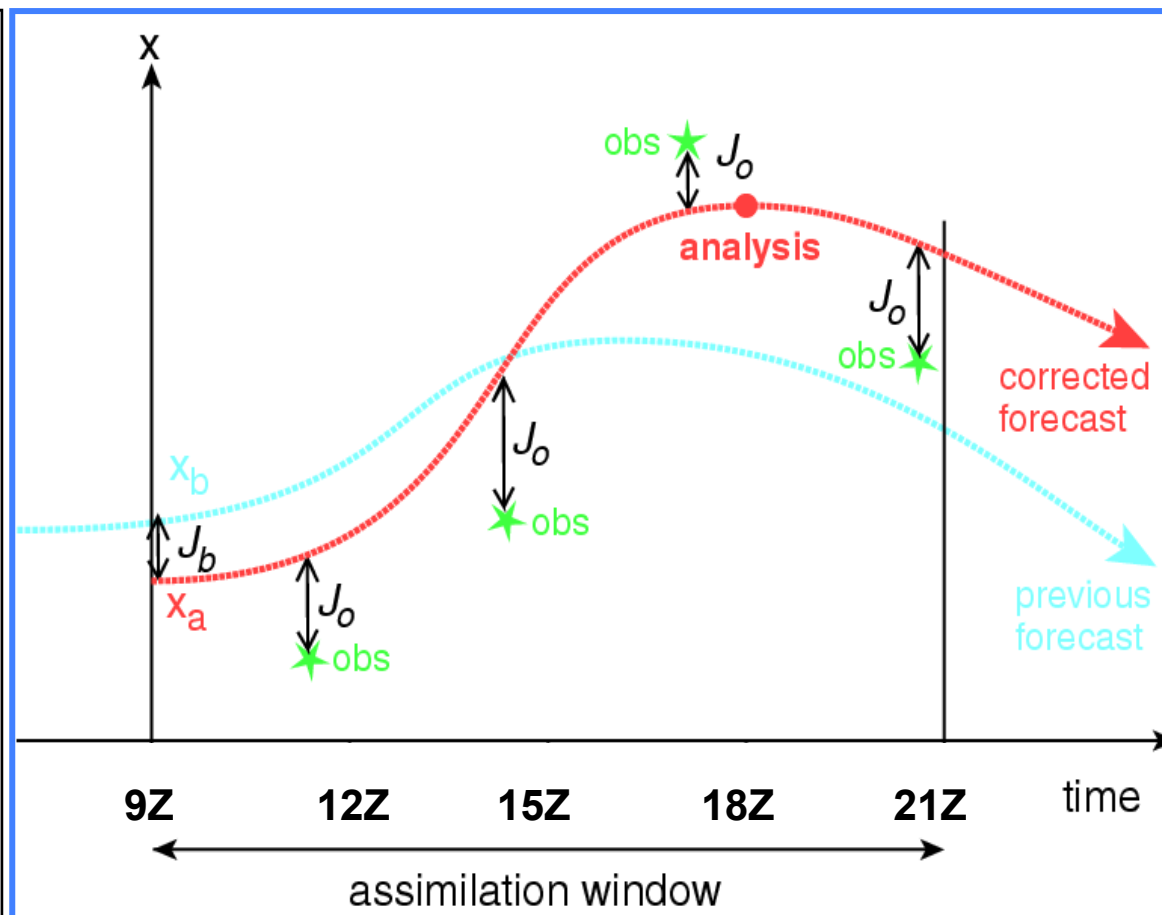


Increments for a single observation of geopotential height at 1000hPa.

A few 4D-Var Characteristics

All observations within a 12-hour period ($\sim 15,000,000$) are used simultaneously in one global (iterative) estimation problem

- ◆ “Observation – model” values are computed at the observation time at high resolution: **16 km**
- ◆ 4D-Var finds the **12-hour** forecast that fits the observations in a dynamically consistent way.
- ◆ Based on a tangent linear and adjoint forecast models, used in the minimization process.
- ◆ **80,000,000** model variables (surface pressure, temperature, wind, specific humidity and ozone) are adjusted



Incremental 4DVar

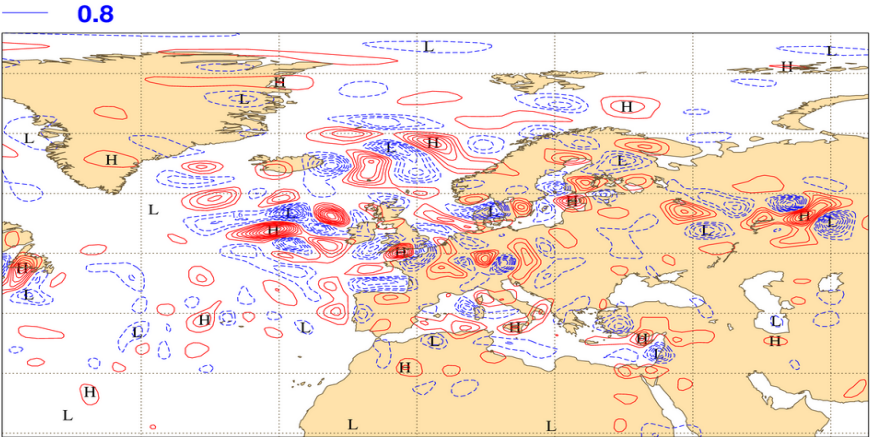
The 4DVar analysis is found by an iterative process in which the difference between the short range forecast model and the observations is minimised in the 12h assimilation window

To reduce the computational cost of 4DVar the minimization is performed at **lower resolution** , in an incremental manner

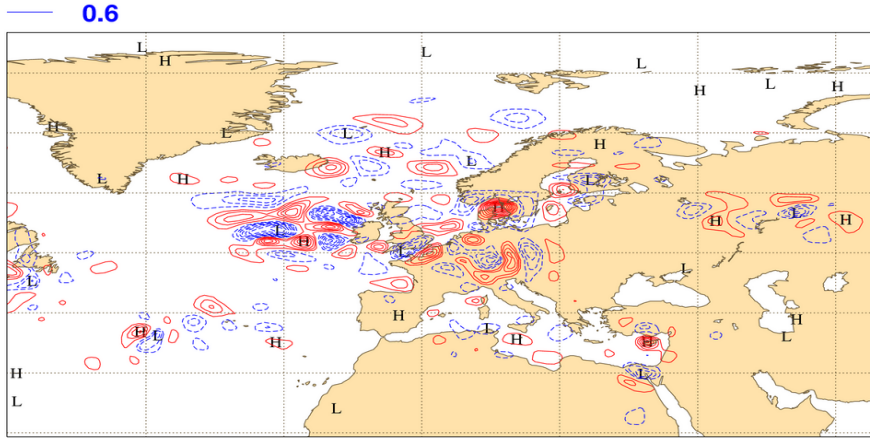
Incremental 4DVar

Analysis increments for vorticity, 500 hPa, 2012/09/30 21UTC

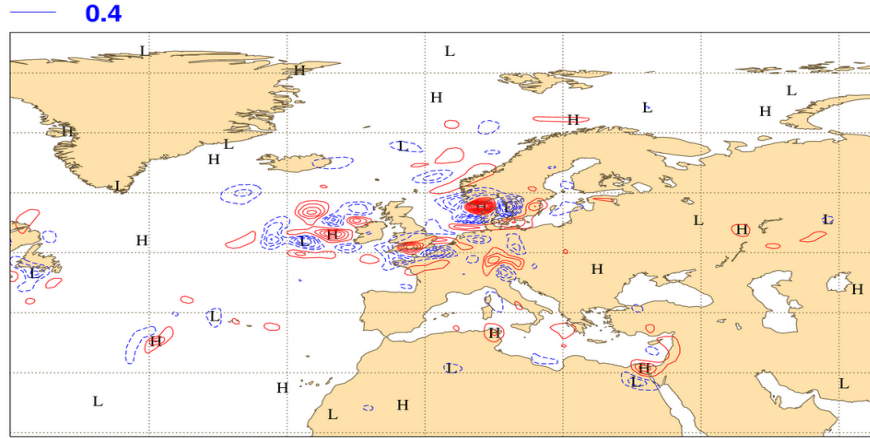
**1st Minimization
T159 (~125 Km)**



**2nd Minimization
T255 (~80 Km)**



**3rd Minimization
T255 (~80 Km)**

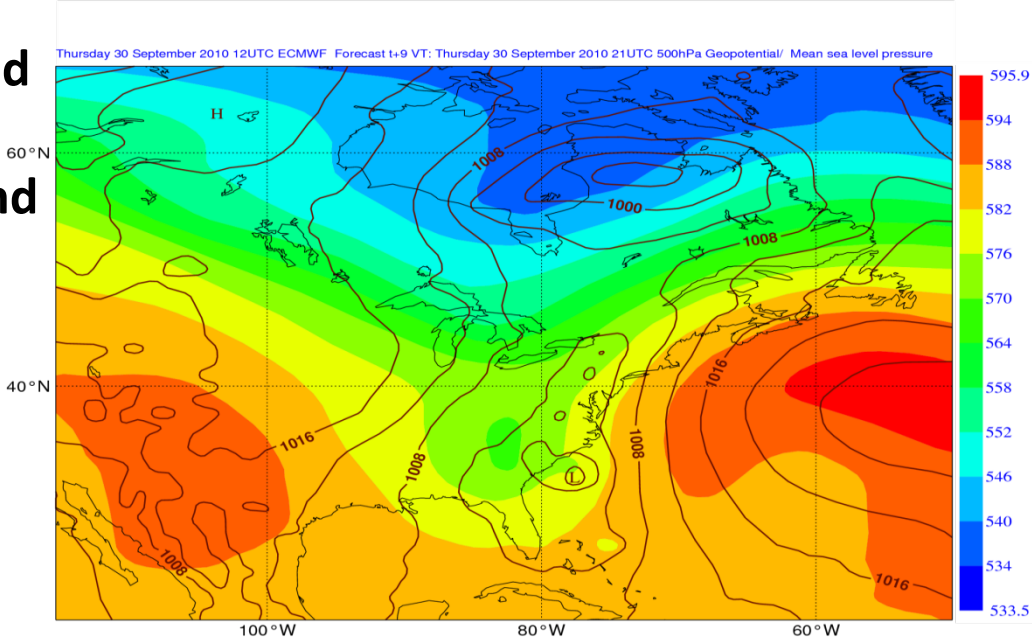


Incremental 4DVar

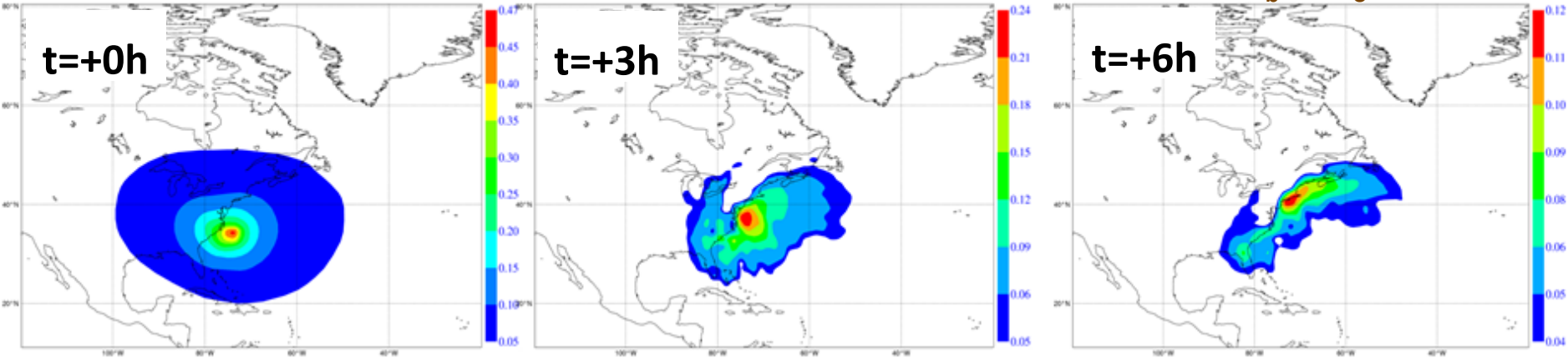
A useful property of 4DVar is that it implicitly evolves the analysis increments *over the length of the assimilation window* (Thepaut *et al.*,1996) in accordance with the model dynamics

Incremental 4DVar

**MSLP (contours) and
500 hPa height
(shaded) background**

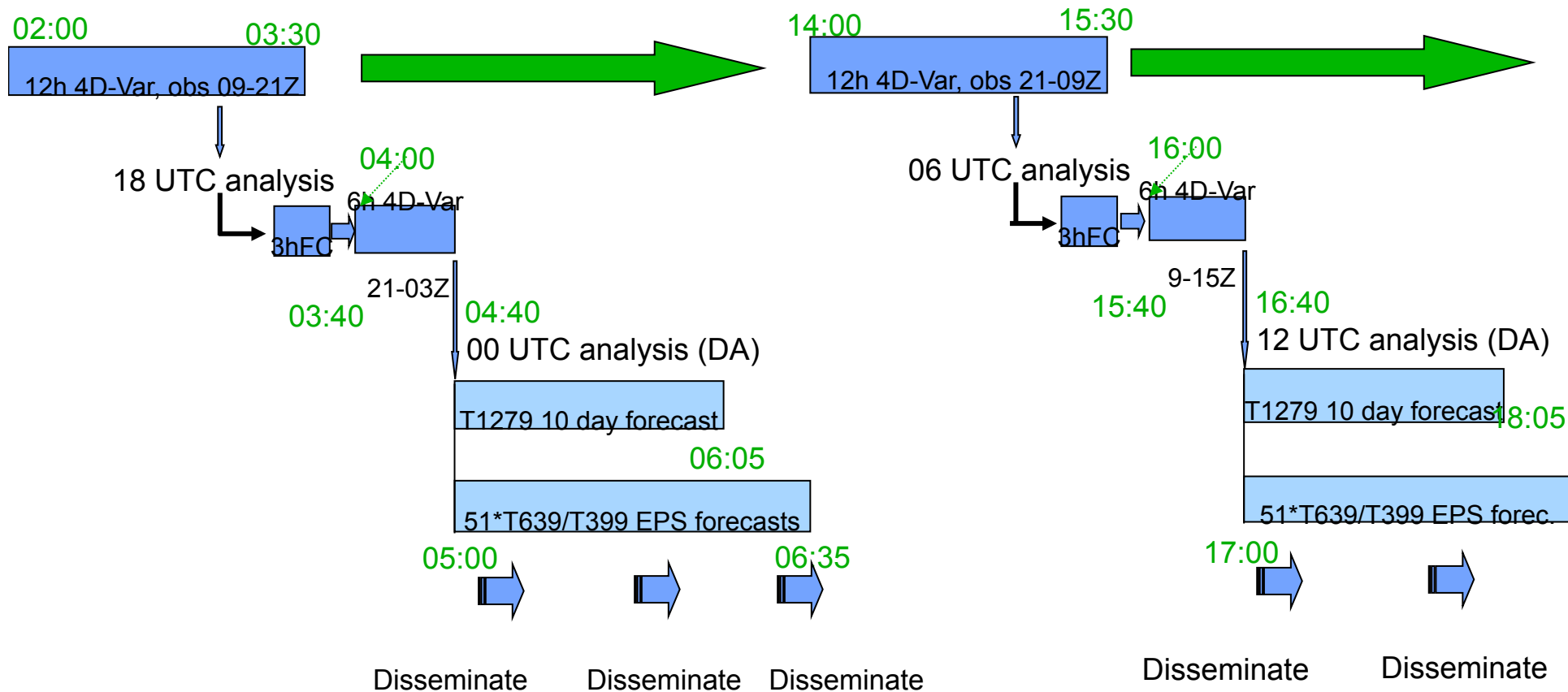


Temperature analysis increments for a single temperature observation at the start of the assimilation window: $x^a(t)-x^b(t) \approx \mathbf{MBM}^T \mathbf{H}^T (\mathbf{y}-\mathbf{H}\mathbf{x}) / (\sigma_b^2 + \sigma_o^2)$



Operational schedule

Early delivery suite introduced June 2004



Recent operational data assimilation changes at ECMWF

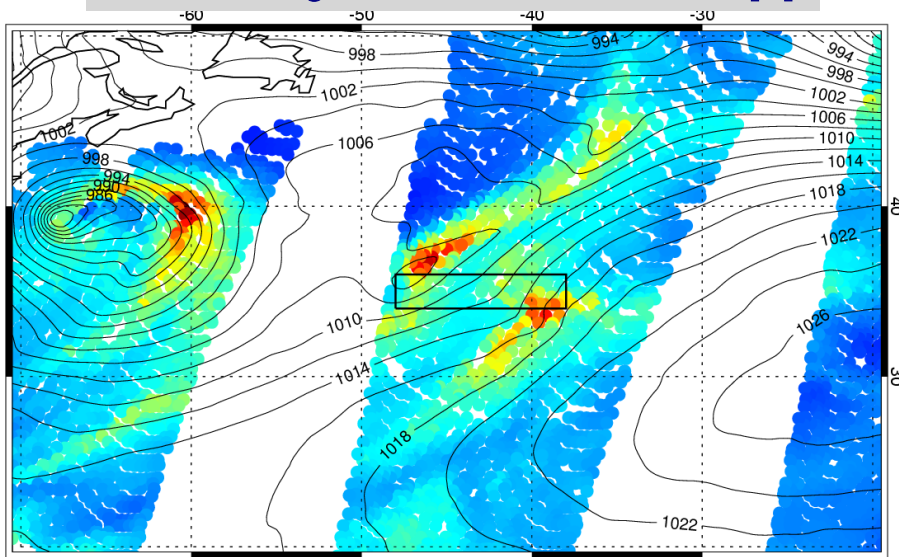
- ◆ Improved humidity analysis, accounting better for super saturation effects
- ◆ Improved scalability – but still more to be done
- ◆ Reduced observation error for AMSU-A radiances
- ◆ Bias correction of aircraft temperature observations
- ◆ Using the data assimilation system for ERA-20C (1900-2010)
- ◆ Assimilation of rain-affected microwave satellite data
- ◆ Use EDA to provide flow-dependent background error variances in 4D-Var
- ◆ Use EDA to provide flow-dependent background error covariances in 4D-Var
- ◆ Extended Kalman Filter (EKF) for soil moisture analysis
- ◆ New snow analysis and higher resolution snow satellite data

Improved assimilation of satellite moisture data

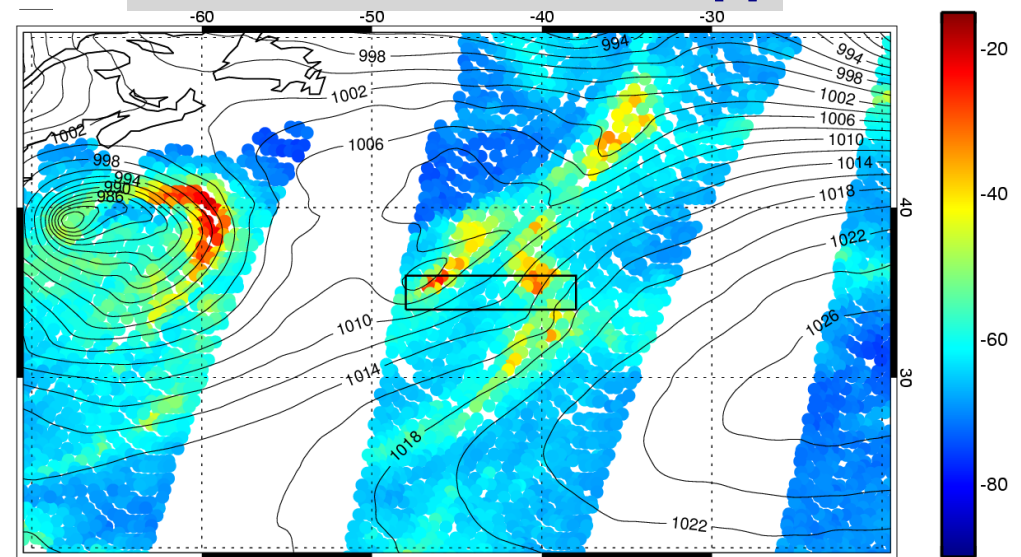
Assimilation of rain-affected microwave

- ◆ First version (SSM/I radiances) 2005; extended to SSMIS, TMI, AMSR-E in 2007
- ◆ Direct 4D-Var radiance assimilation from March 2009; improved 2010; improved 2011
- ◆ Main difficulties: inaccurate moist physics parameterizations (location/intensity), formulation of observation errors, bias correction, linearity.

4D-Var first guess SSM/I ΔT_b 19v-19h [K]



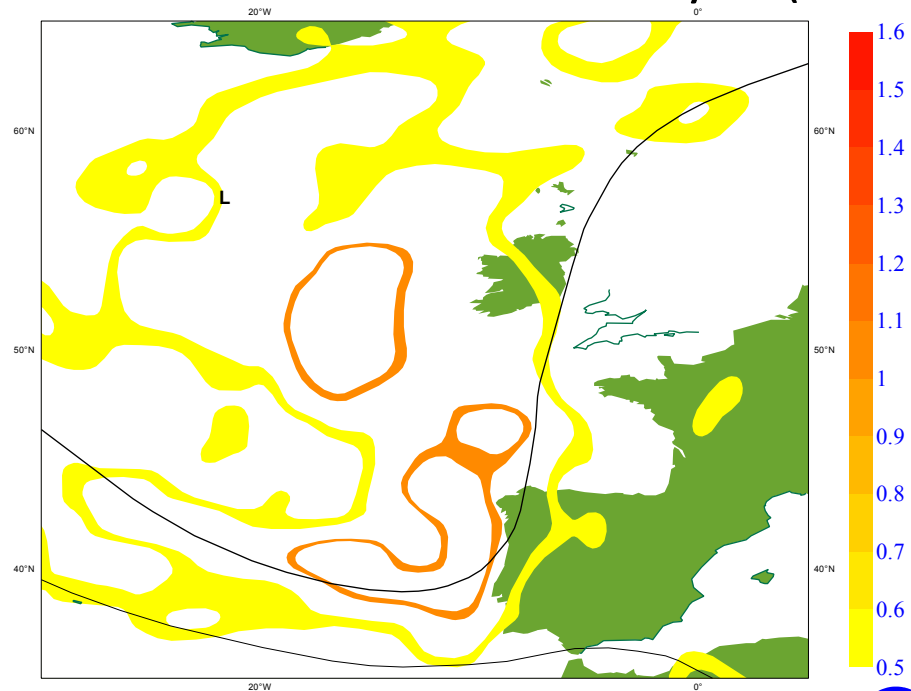
SSM/I observational ΔT_b 19v-19h [K]



Ensemble of Data Assimilations (EDA)

- ◆ Run an ensemble of analyses with perturbed observations, perturbed model physics and perturbed Sea Surface Temperature fields.
- ◆ 25 EDA members plus a control at lower resolution.
- ◆ Form differences between pairs of analyses (and short-range forecast) fields.
- ◆ These differences will have the statistical characteristics of analysis (and short-range forecast) error.

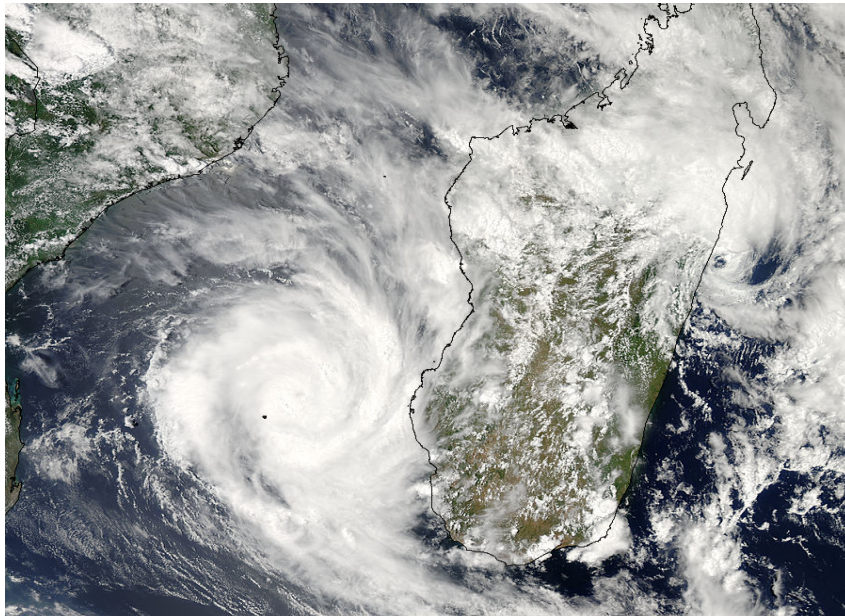
Yellow shading where the short-range forecast is uncertain: This will give observations more weight in these regions.



In May 2011 ECMWF implemented EDA based flow-dependent background error variance in 4D-Var

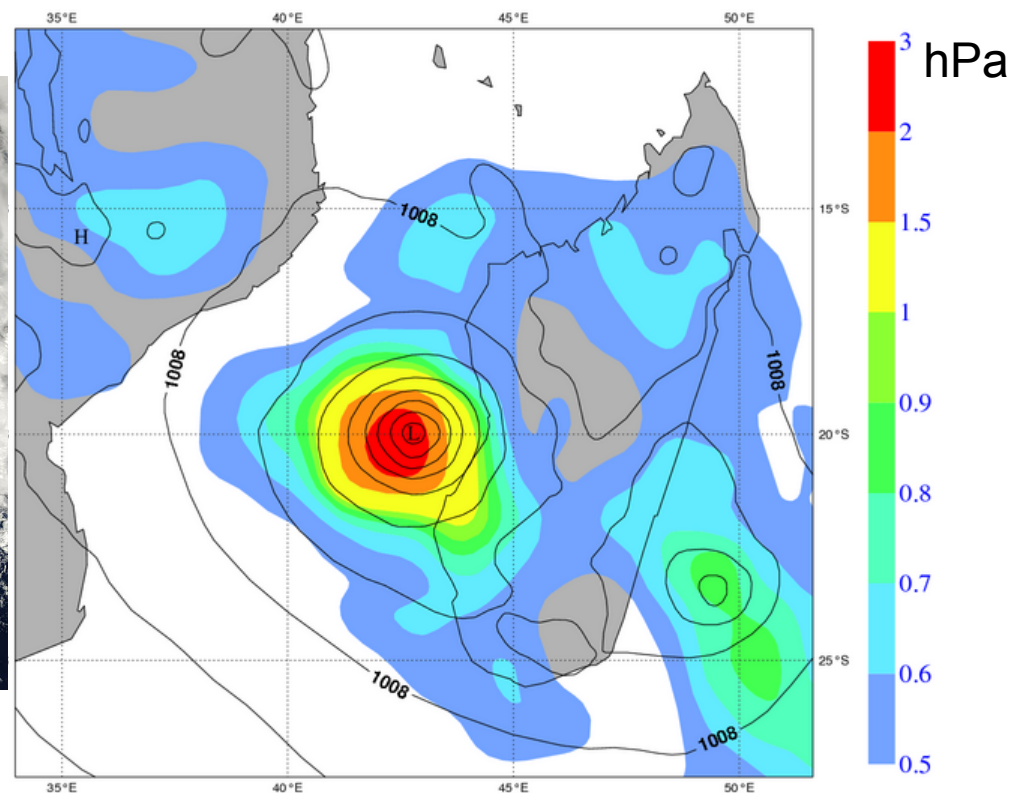
The 10-member EDA has been used to estimate the background error variance in the deterministic 4D-Var.

EDA based background error variance for Surface pressure



Hurricane Fanele, 20 January 2009

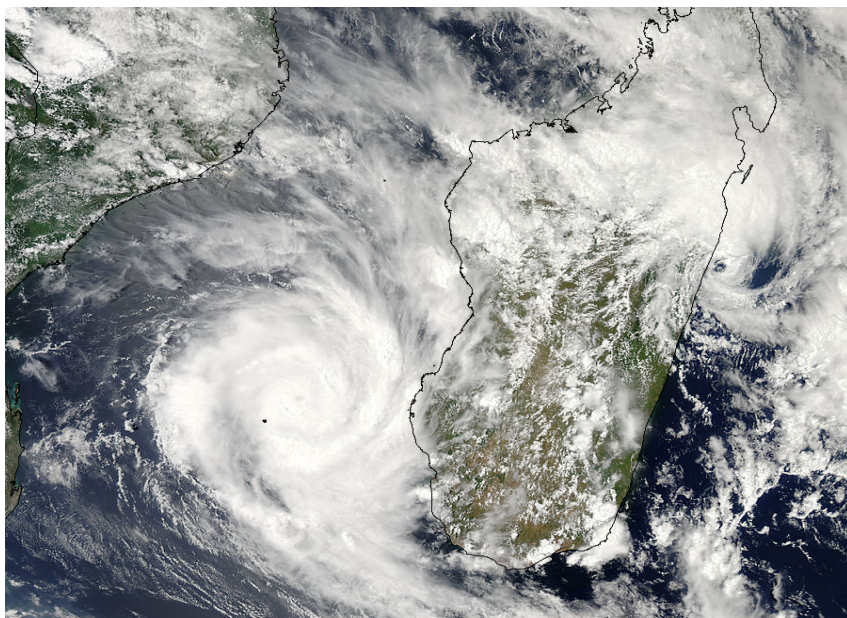
Tuesday 20 January 2009 00UTC ECMWF Forecast t+9 VT: Tuesday 20 January 2009 09UTC Surface: Mean sea level pressure



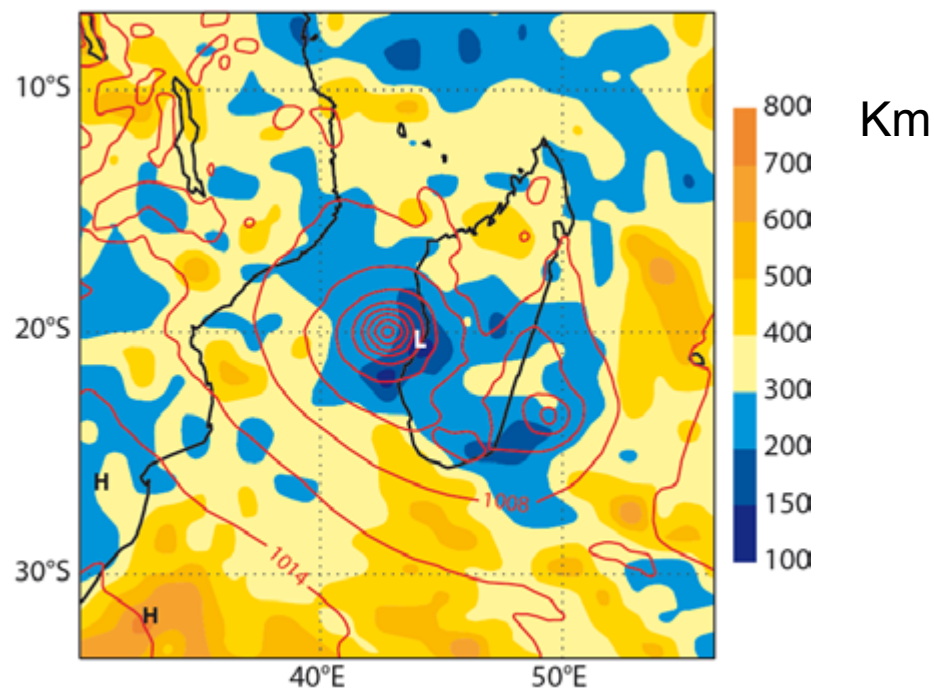
In November 2013 ECMWF will implement EDA based flow-dependent background error **covariances** in 4D-Var

The 25-member EDA has been used to estimate the background error covariance in 4D-Var.

EDA based background error covariance length scale for Surface pressure



Hurricane Fanele, 20 January 2009

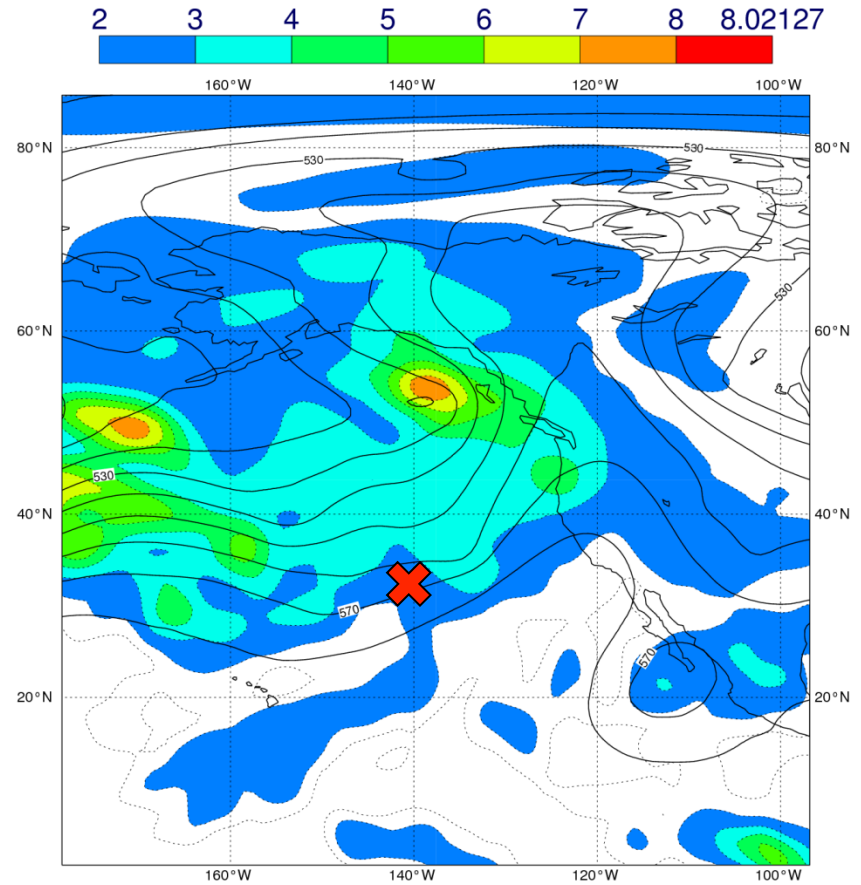
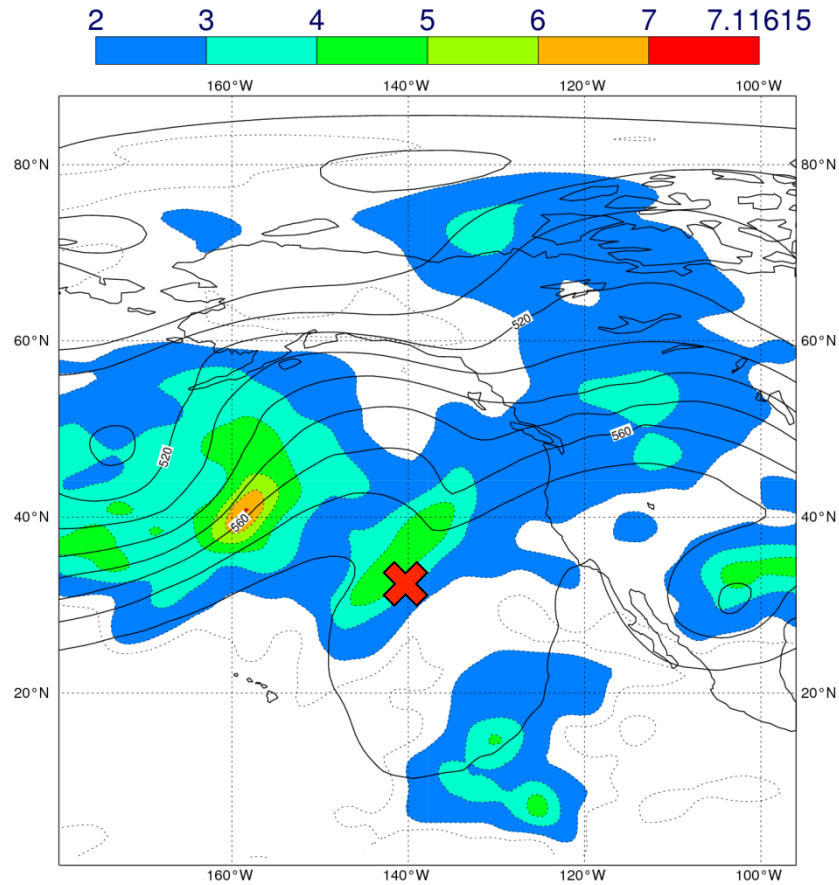


Why are flow-dependent covariances important?

Vertical correlations

2012-01-01 00Z

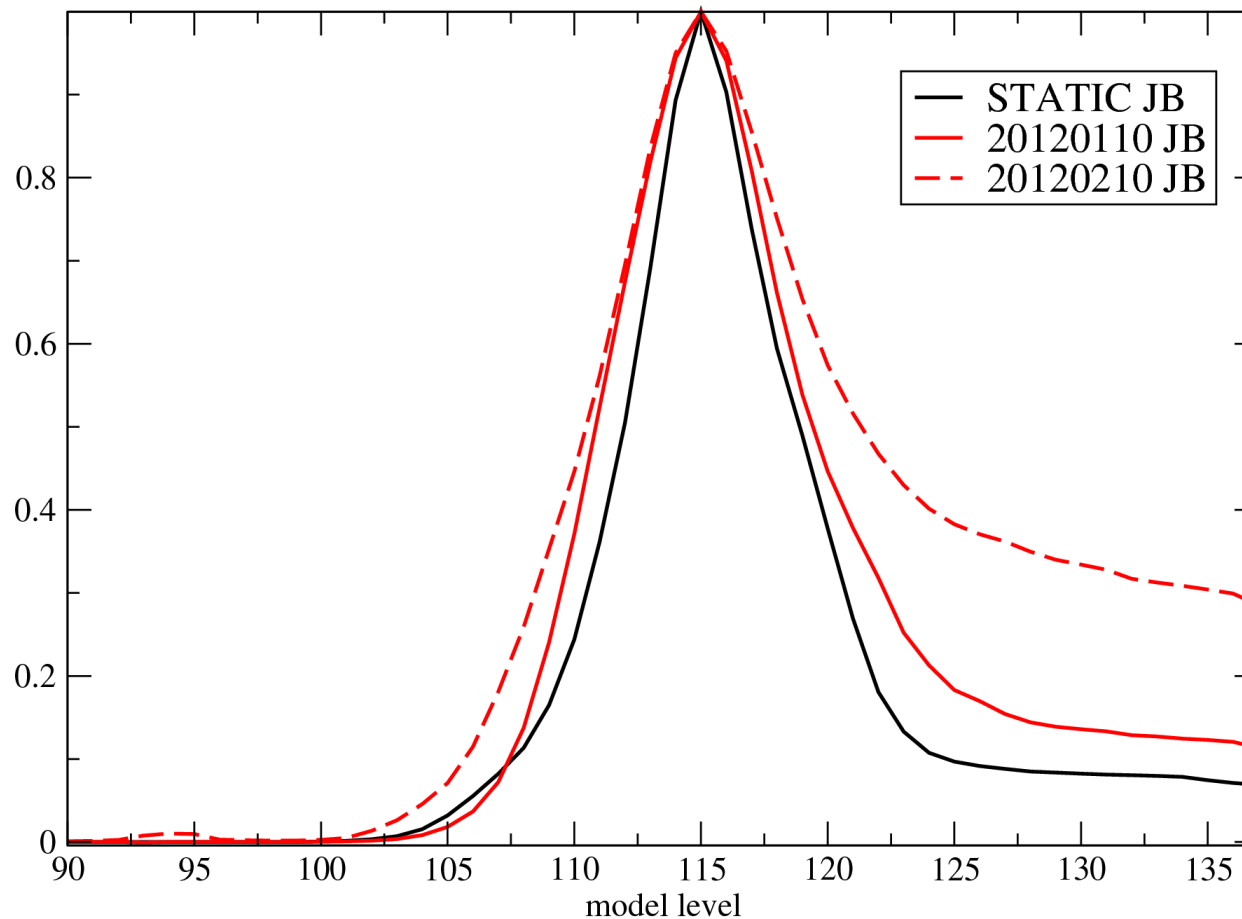
2012-02-01 00Z



Why are flow-dependent covariances important?

Vertical correlations

Vorticity vertical correlation at (30N,140W) ml=115



Why implementing Ensemble of Data Assimilations?

- ◆ **In general to estimate analysis and short range forecast uncertainty**
- ◆ To improve the initial perturbations in the Ensemble Prediction (implemented June 2010)
- ◆ To calculate static and seasonal background error statistics
- ◆ To estimate flow-dependent background error in 4D-Var - “errors-of-the-day” (implemented May 2011)
- ◆ To improve QC decisions and improve the use of observations in 4D-Var (implemented May 2011)
- ◆ To estimate flow-dependent background error covariances in 4D-Var - “errors-of-the-day” (implementation: November 2013)

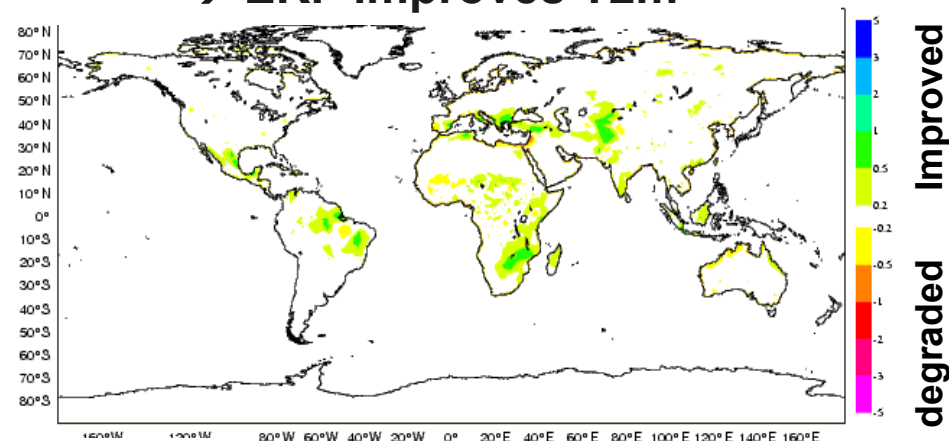
Soil moisture assimilation using Extended Kalman Filter Implemented in November 2010

Impact on 2-metre Temperature

Compared to the old OI analysis, the simplified Extended Kalman Filter consistently improves T2m

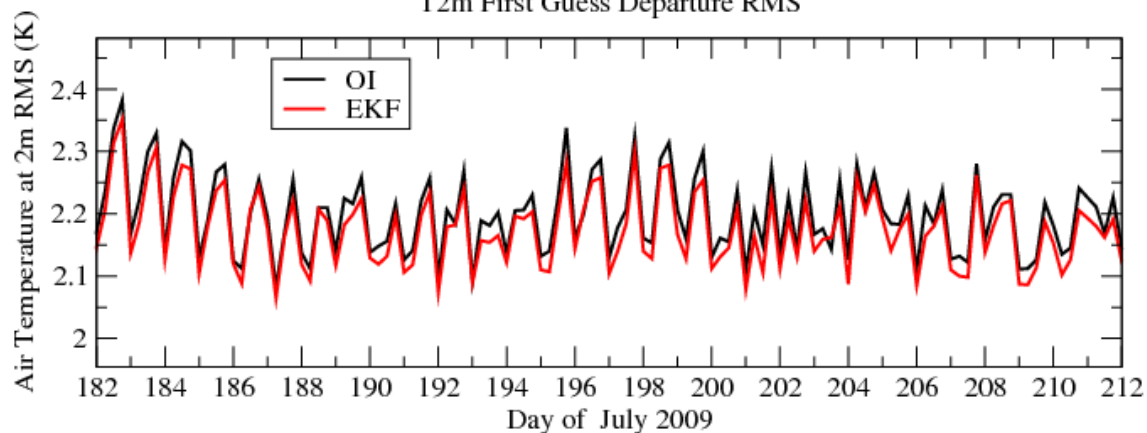
T2m error (OI-SEKF) 48h fc

→ EKF improves T2m



Global mean RMS (against SYNOP)

T2m First Guess Departure RMS



November 2010: new Optimum Interpolation snow analysis

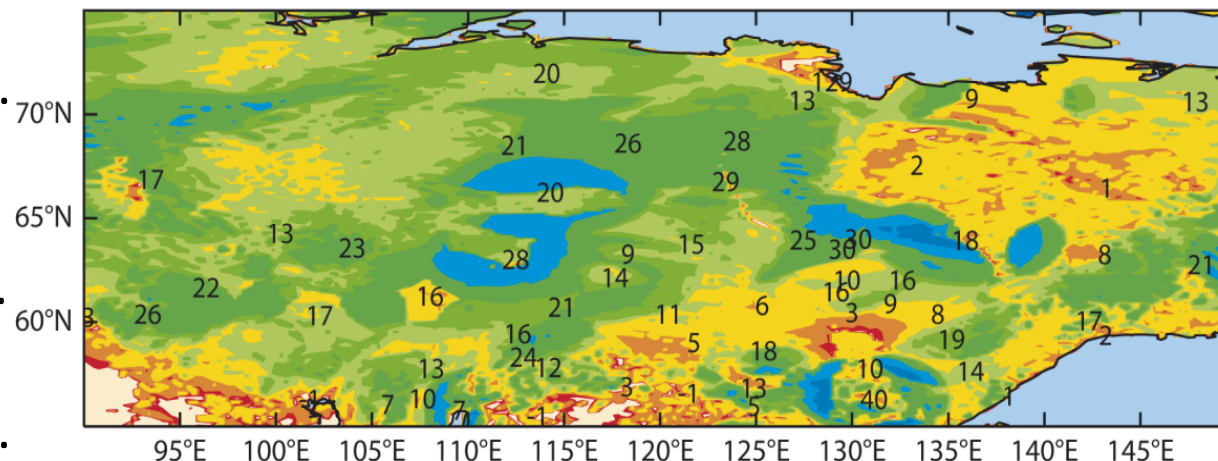
Snow depth (cm) analysis and SYNOP reports on 30 October 2010 at 00 UTC

The change improves the snow analysis significantly.

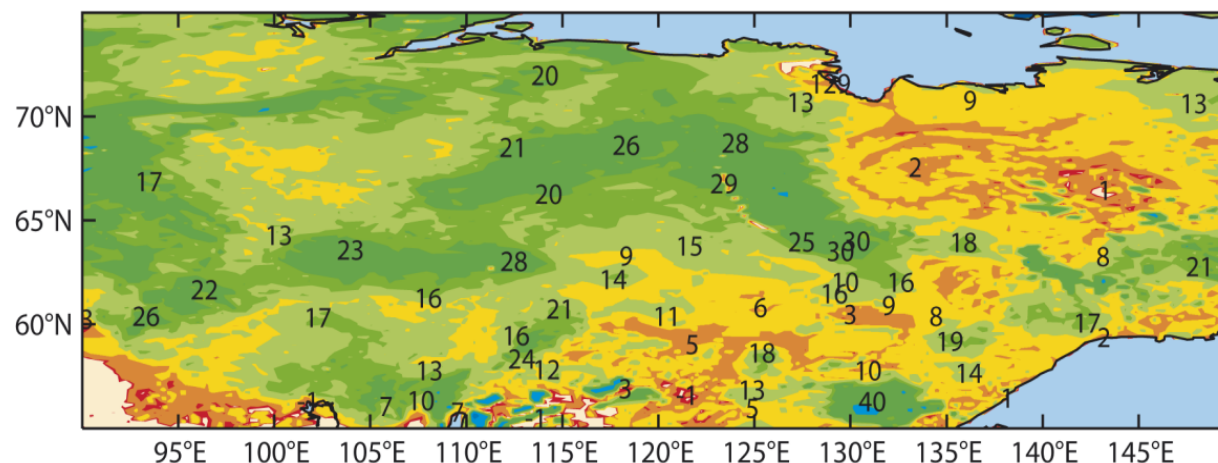
Spurious patterns and serious shortcomings of previous scheme resolved.

Better agreement with SYNOP snow observations.

a 36r2 osuite



b 36r4 esuite



- Top: Old Cressman using 24km NESDIS data

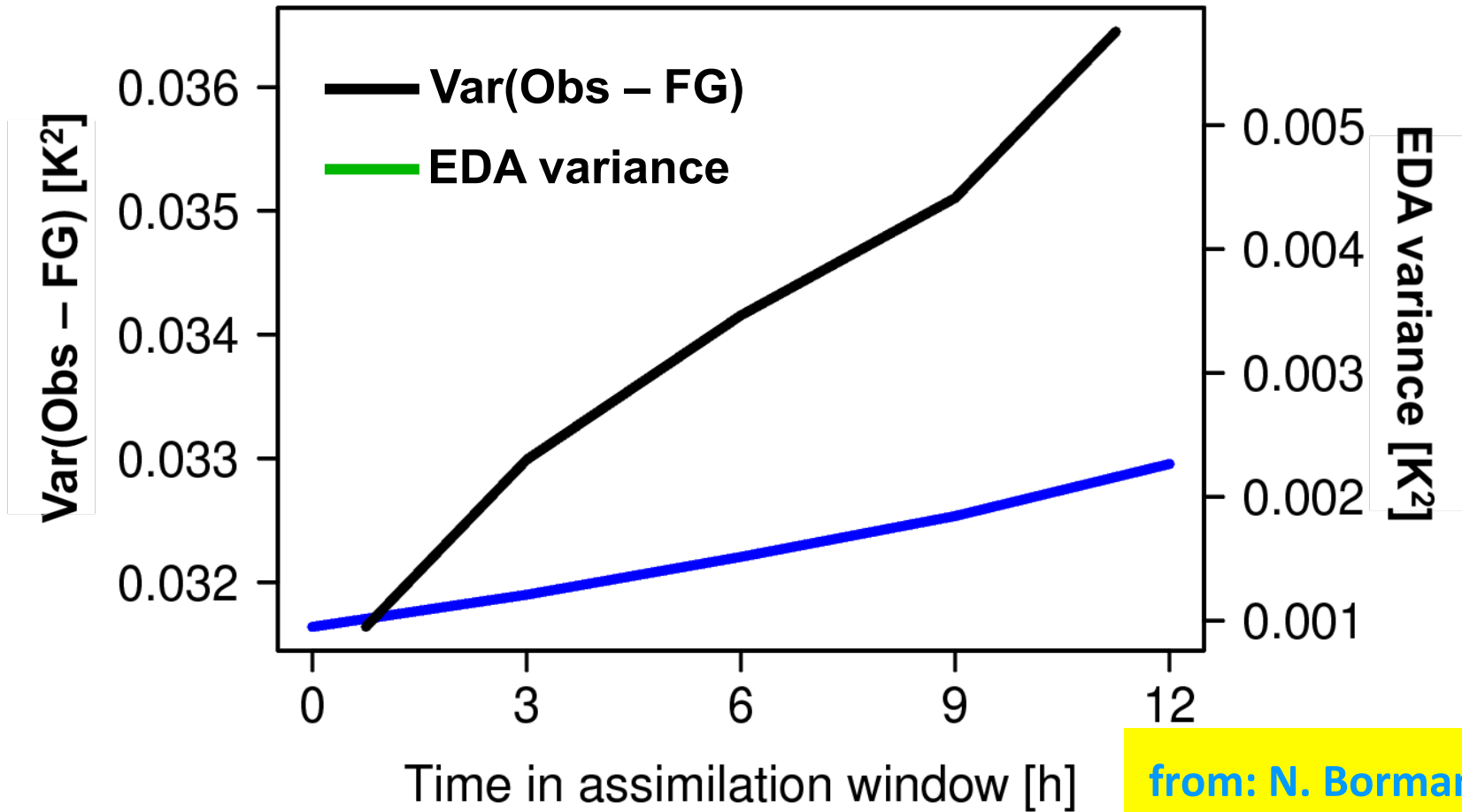
- Bottom: New OI (Brasnett 1999) approach using 4km NESDIS data

Coming soon in the data assimilation system at ECMWF

- ◆ Use of ASCAT data in EKF soil moisture analysis
- ◆ Introduction of cloud condensate in the data assimilation
- ◆ Retune observation errors for all data types
- ◆ A move to an Object Oriented Prediction System
- ◆ Improved scalability of 4D-Var
- ◆ Improvements to the EDA: model error parameterization, SST perturbations
- ◆ Improvements to the Jb formulation: anisotropic correlations, balance between q-T increments
- ◆ COPE – Continuous observation processing environment
- ◆ Long window 4D-Var: extend to 24 hour window

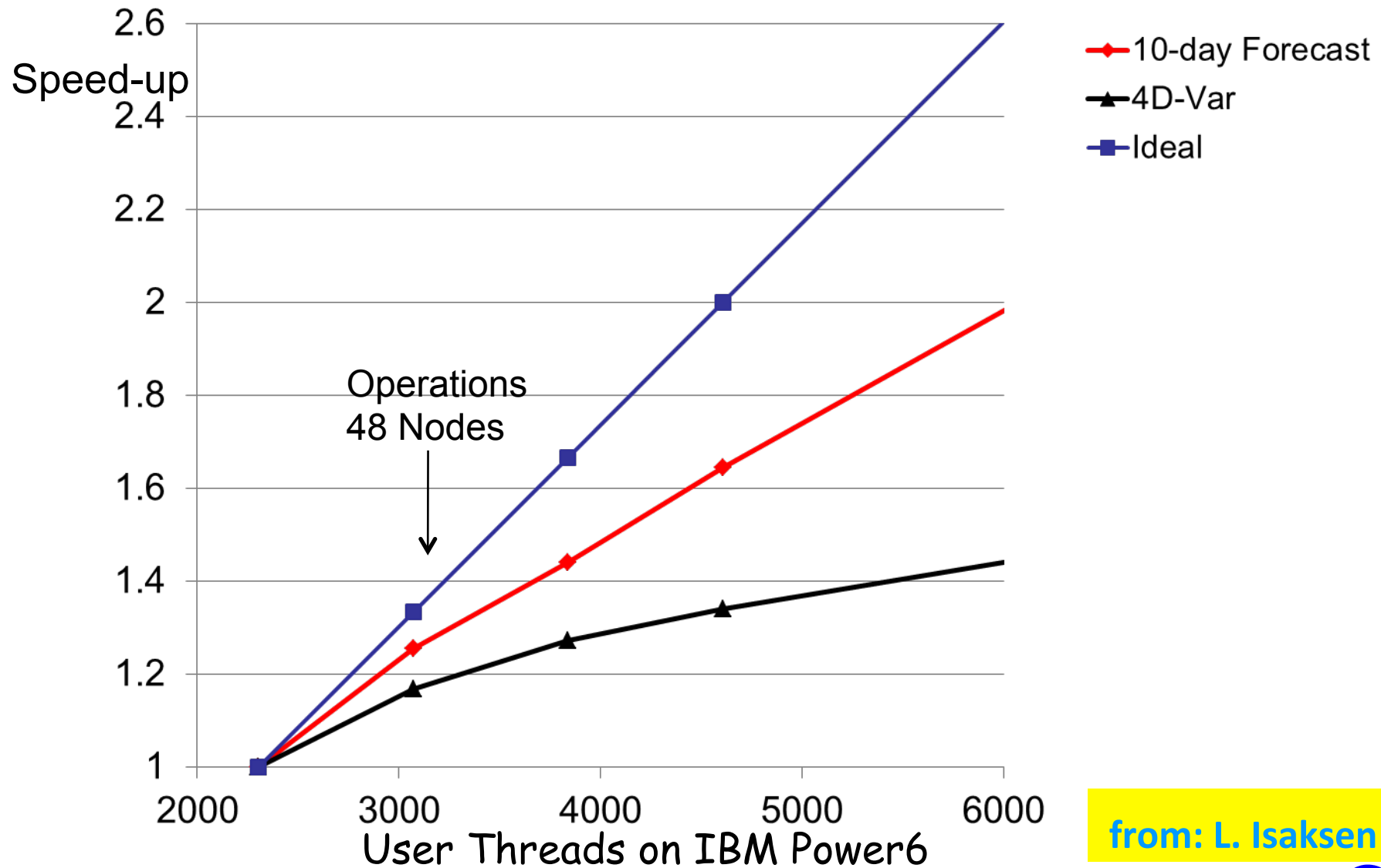
Evolution of EDA in assimilation-window

Example: AMSU-A, channel 8 (100-300 hPa)



from: N. Bormann

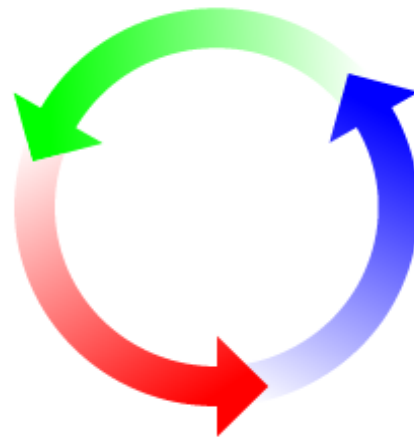
Scalability of T1279 Forecast and 4D-Var



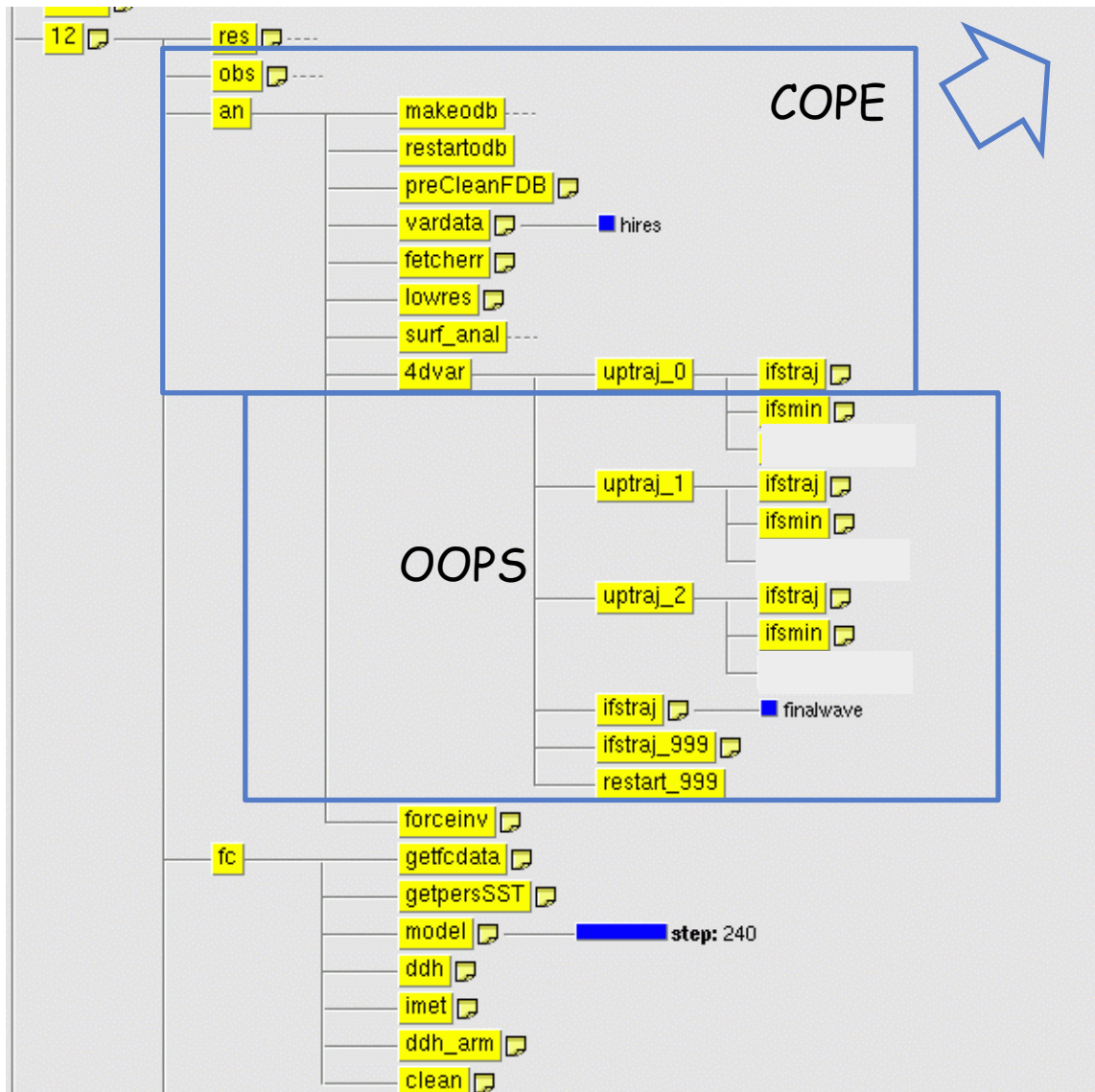
from: L. Isaksen

Continuous Observation Processing Environment (COPE)

- Implement a hub Observation Data Base (ODB) interface
- Shortens the time critical path by performing observation pre-processing and screening as data arrive
- Improve scalability by removing most observation related tasks from time critical path
- Reduce risk of failures in the analysis during the time critical path
- Enables near real-time quality control and monitoring of observations
- More modular software



Improving scalability of time critical Data Assimilation suite



COPE

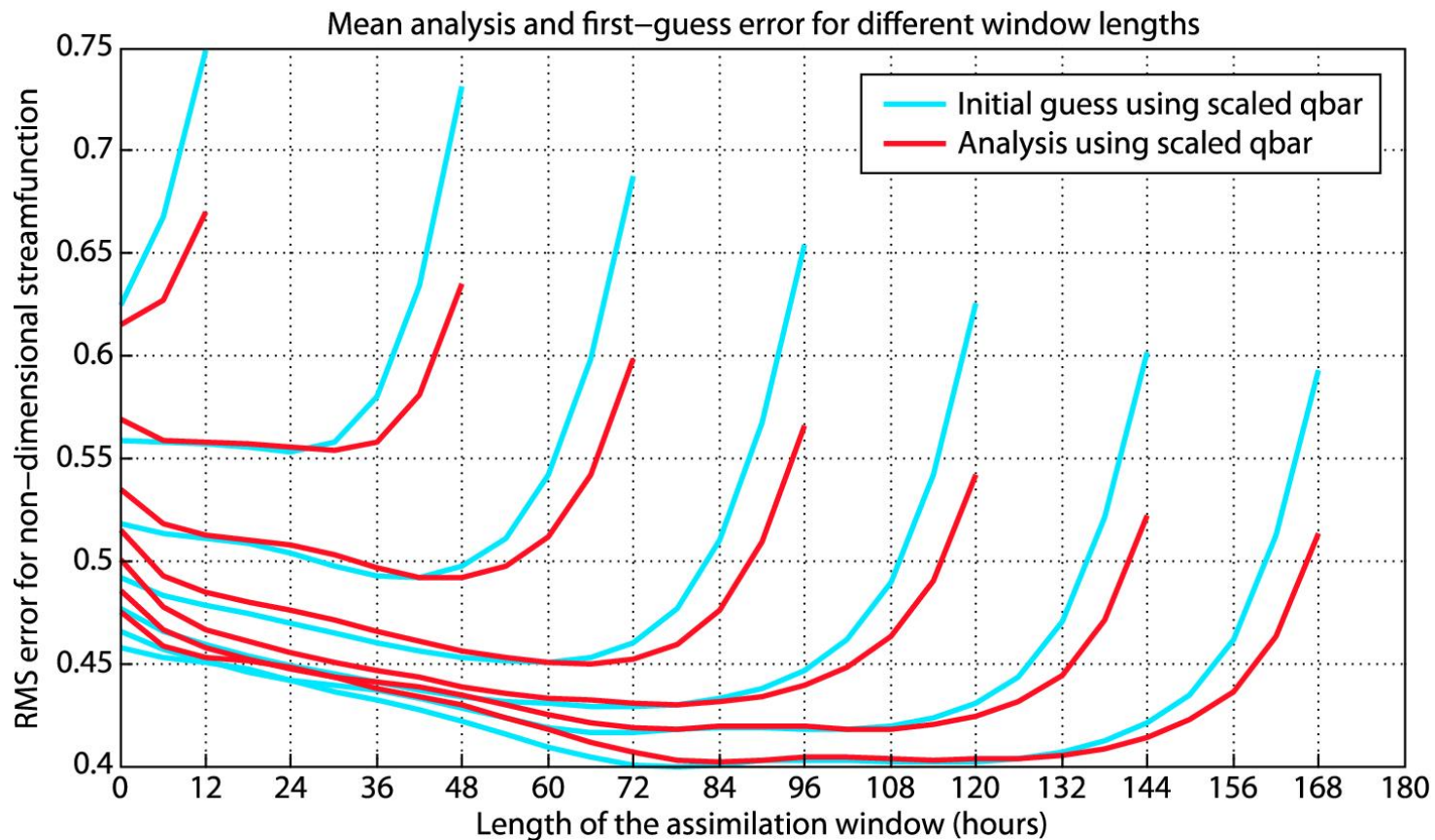
**(Continuous Observation
Processing Environment)**

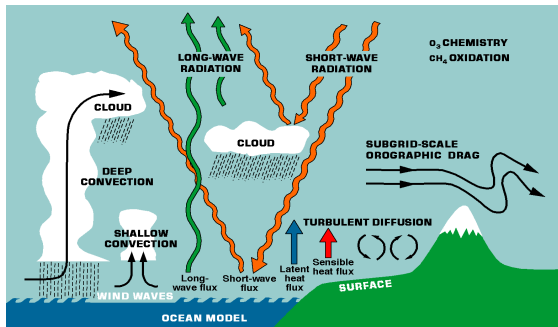
OOPS

**(Object-Oriented
Prediction System)**

Long-window, weak-constraint 4D-Var - a longer-term project

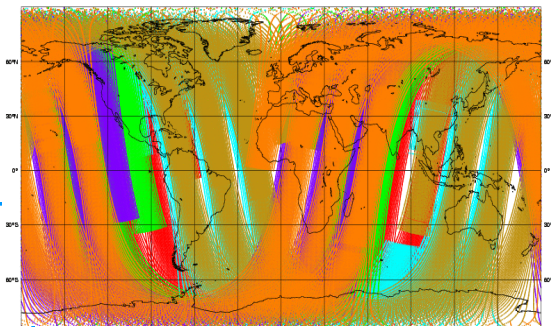
Results based on a two-layer quasi-geostrophic model indicates that increasing the length of the analysis window is beneficial, even with a very simple model error representation.



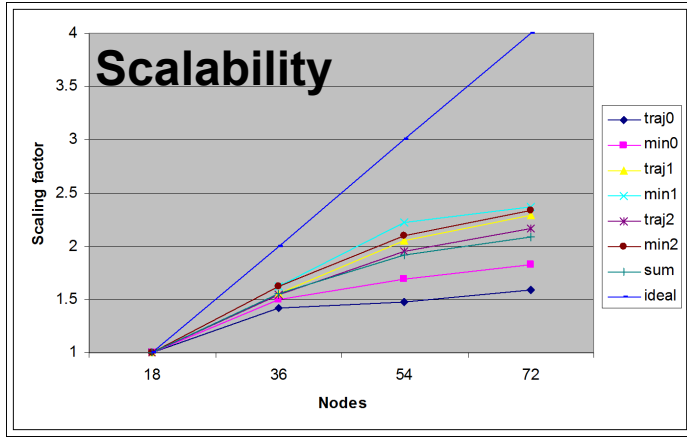
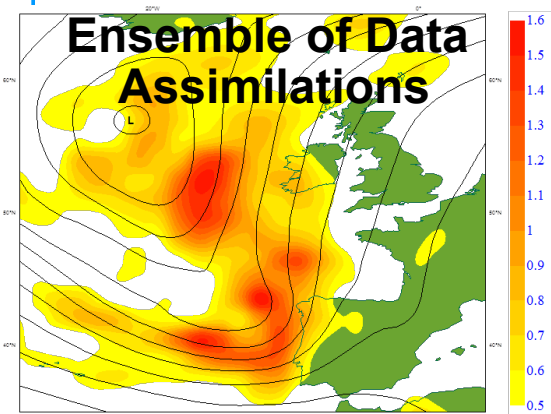
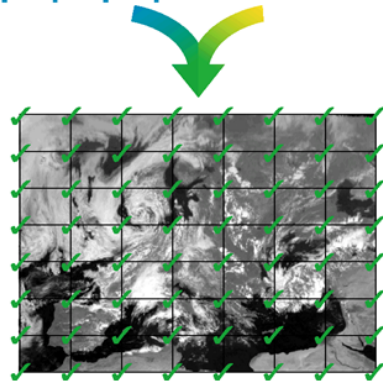
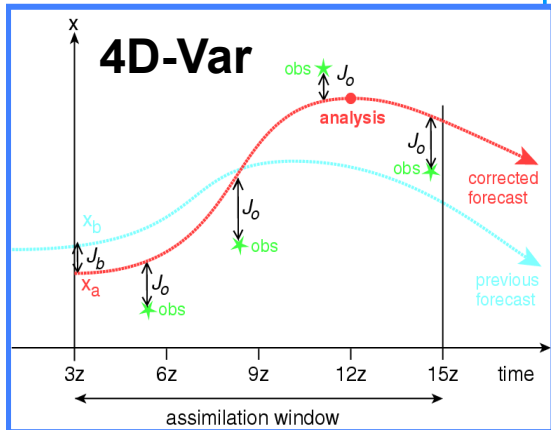
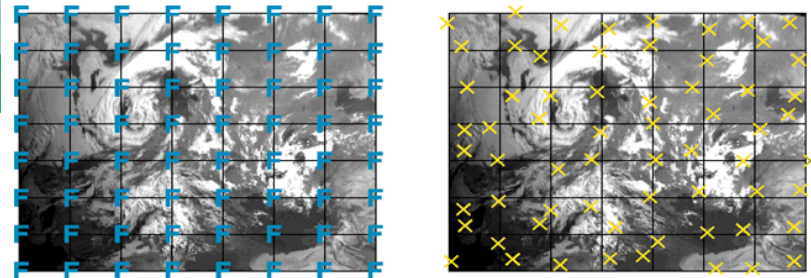


Forecast model

Data assimilation at ECMWF



Observations



Methods Progress and plans

